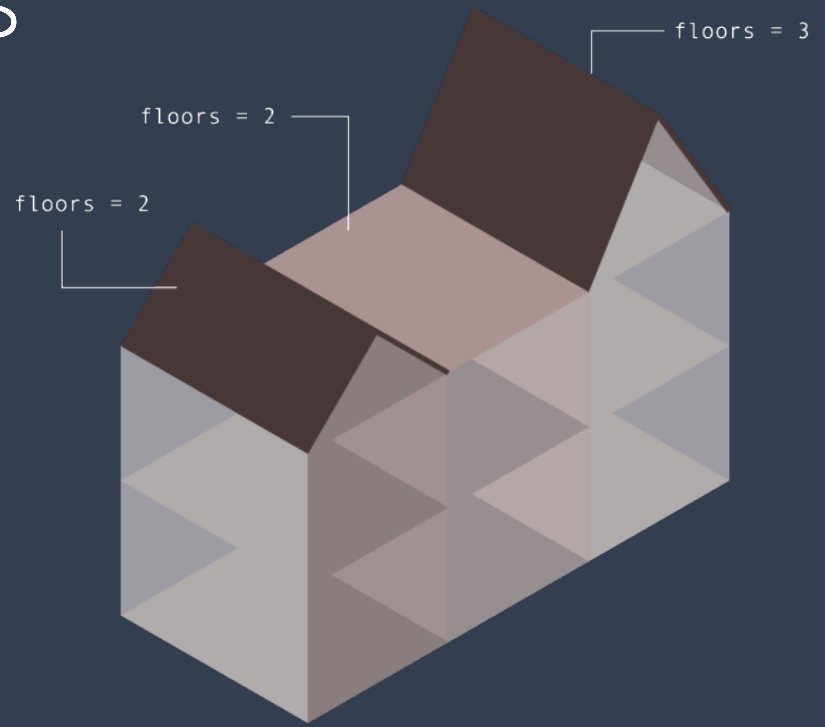
MSc Thesis in Geomatics

# Inferring the number of floors of building footprints in the Netherlands

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13th January 2022

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Faculty of Architecture
and the Built Environment

# Topic relevance

## Energy demand estimation

Image: https://nos.nl/artikel/2352272-europese-commissie-komt-met-renovatiegolf-voor-huizen-vanwege-klimaat.html

## Building population estimation

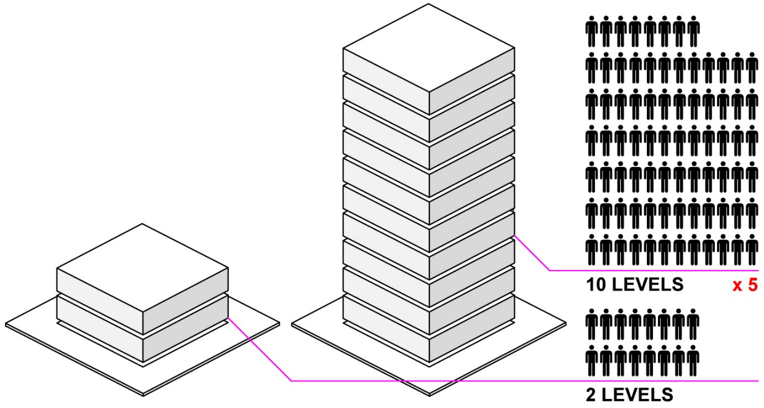
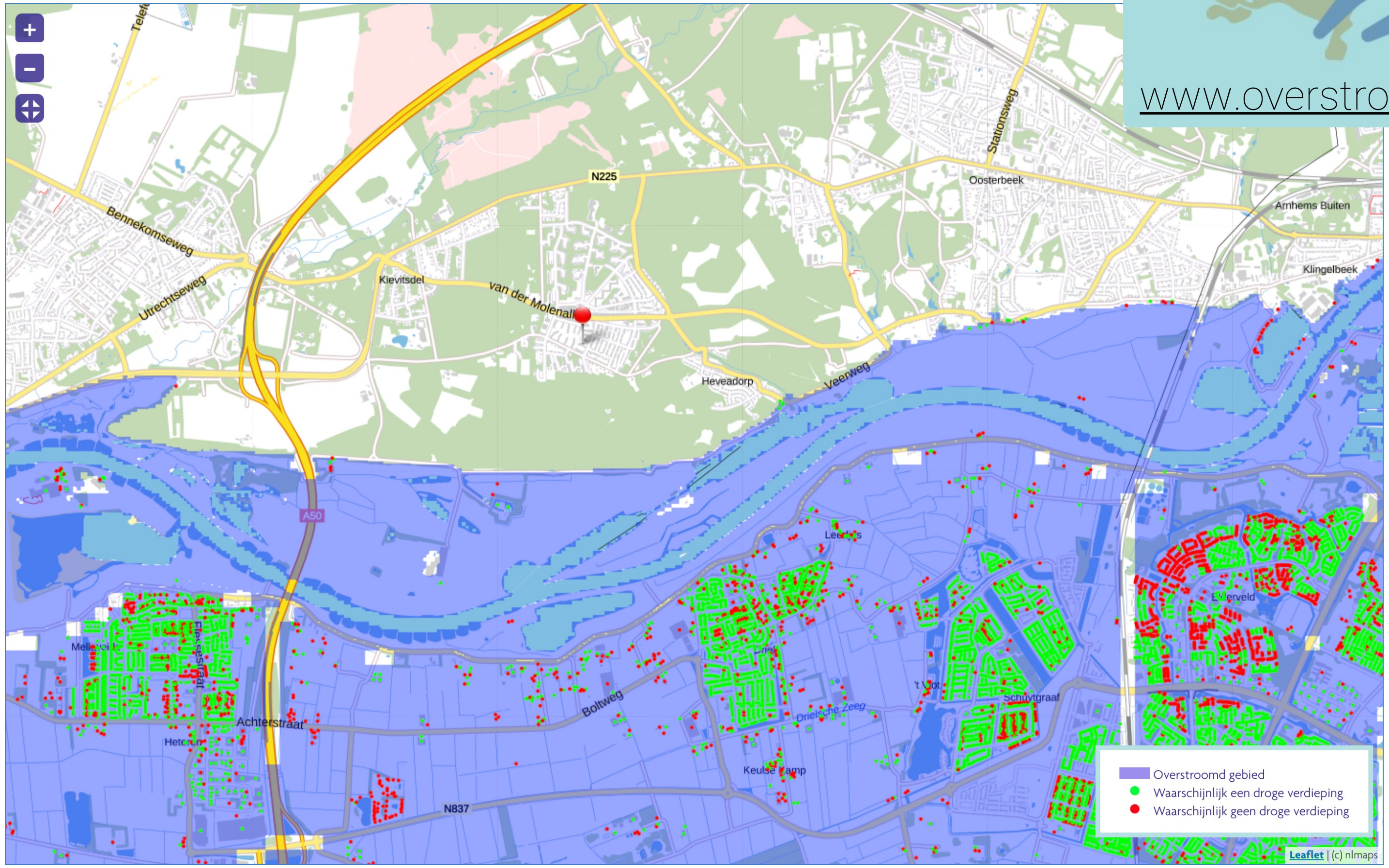



Image: https://densityarchitecture.wordpress.com/2013/01/18/understanding-density/

## Flood response plans

Image: https://www.eoi.es/blogs/imsd/let-the-flood-come-dutch-urban-planning/

# Topic relevance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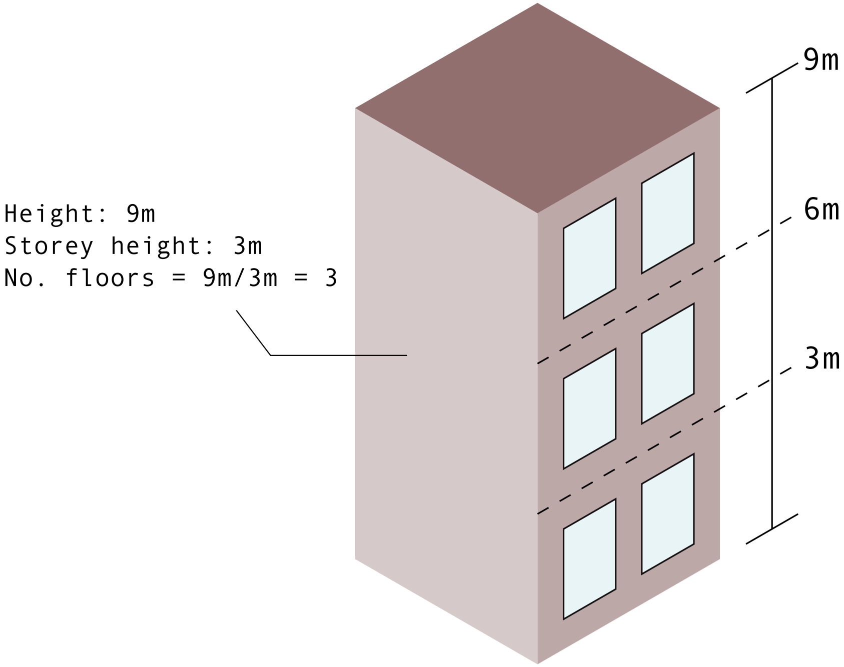
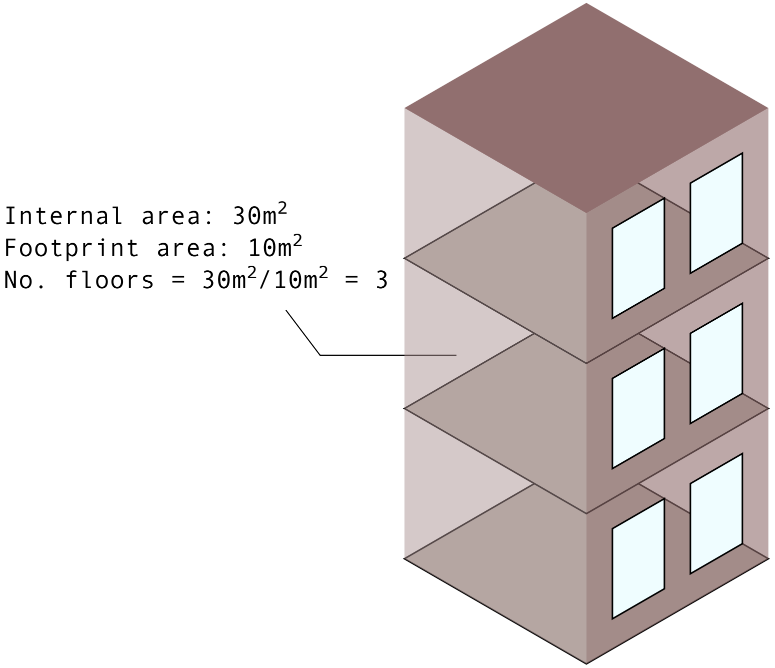
# Current approach

## Height-based




## Area-based



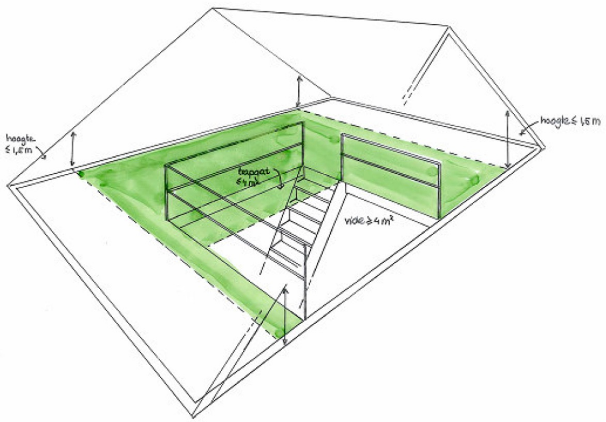
# Limitations of current approach

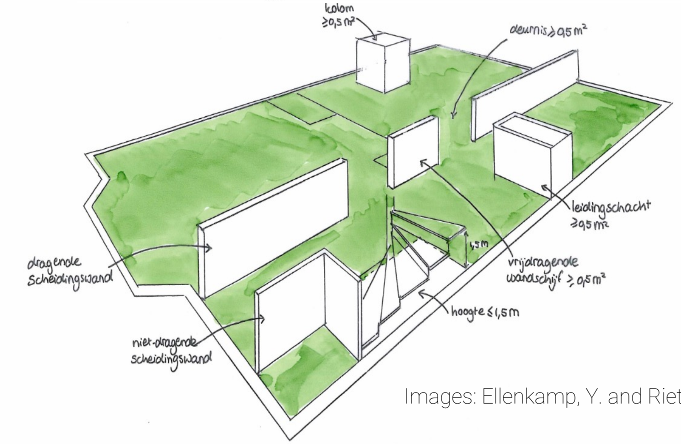
## Height-based

Actual: 1 floor
Calculated: 2 floors

Actual: 8 floors
Calculated: 9 floors

## Area-based




Images: Ellenkamp, Y. and Rietdijk, M. (2010)

# Research objectives

# Research questions

To what extent can **machine learning** provide a **better estimate** of the number of floors than a **purely geometric** approach?

a) Which **features** are related to the number of floors? Is there any **overlap** between these features and which subset yields the **best** results?

b) Which **machine learning algorithm** provides the **best** results? How are the results affected by **feature subsets** that reflect different levels of **data availability**?

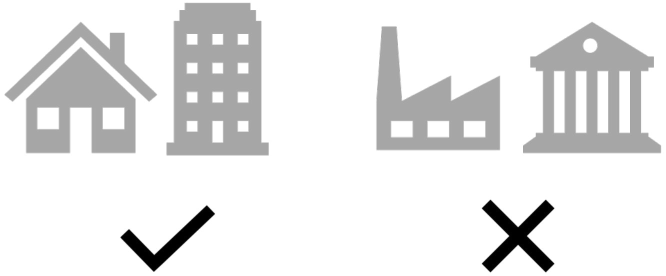
c) What **level of performance** can be achieved compared to a **purely geometric approach**? What types of **gross errors** are present?

d) Since floor count is generally an integer value, is this a **regression or classification** problem? If considered regression, how does **rounding** the predictions affect the results?

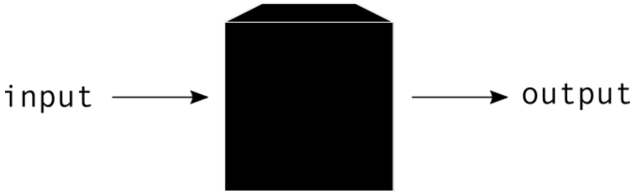
# Scope

(1) NL

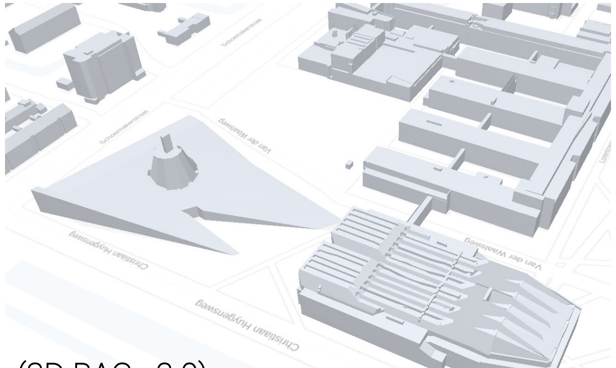
(2) (Mixed-)residential buildings



(3) Algorithm ≠ black-box




(4) No geometric modelling



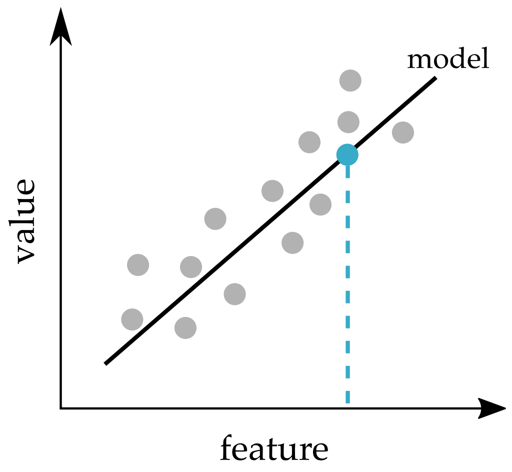
(3D BAG v2.0)

# Background

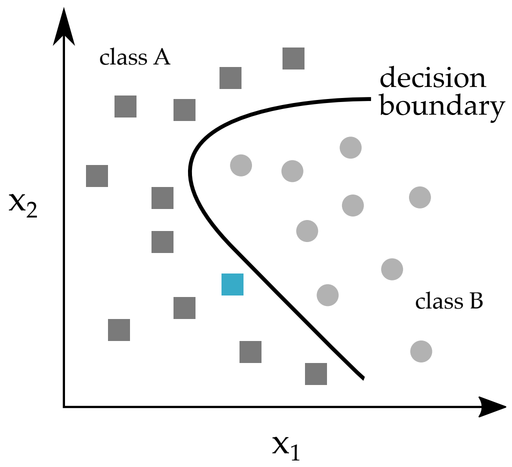
# Machine learning

## Supervised learning

### Regression



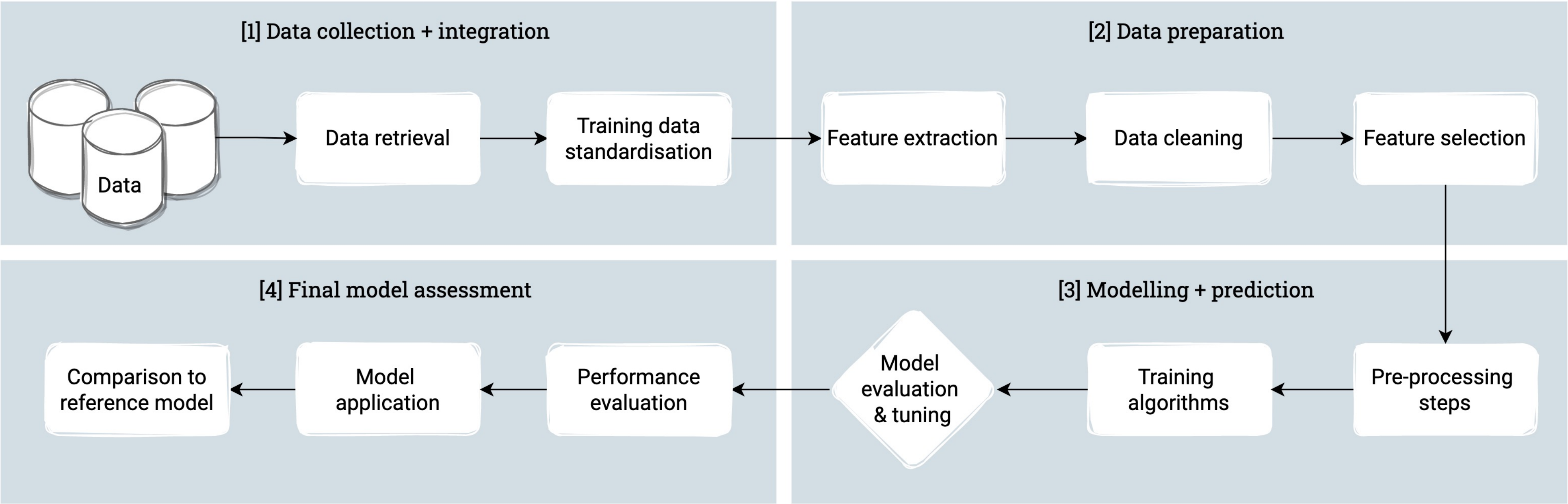

### Classification



# Methodology

- Research objectives
- Background
- Methodology
- Implementation
- Results
- Conclusions

# Overview methodology



# Extracted features

| Cadastral | Census |
|---|---|
| - Construction year | - Population density |
| - Building function | - % multi-household buildings |
| - Net internal area | - Average no. cafes in 1km |
| - No. units | |

| 2D geometric | 3D geometric |
|---|---|
| - Area | - Volume |
| - Perimeter | - Roof surface area |
| - No. vertices | - Wall surface area |
| - No. neighbours in 100m | - Building height |
| - No. adjacent buildings | - Ridge – eave height |
| | - Roof shape |

Image: Biljecki et al. (2014)

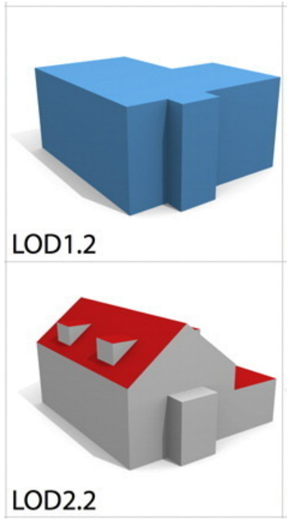
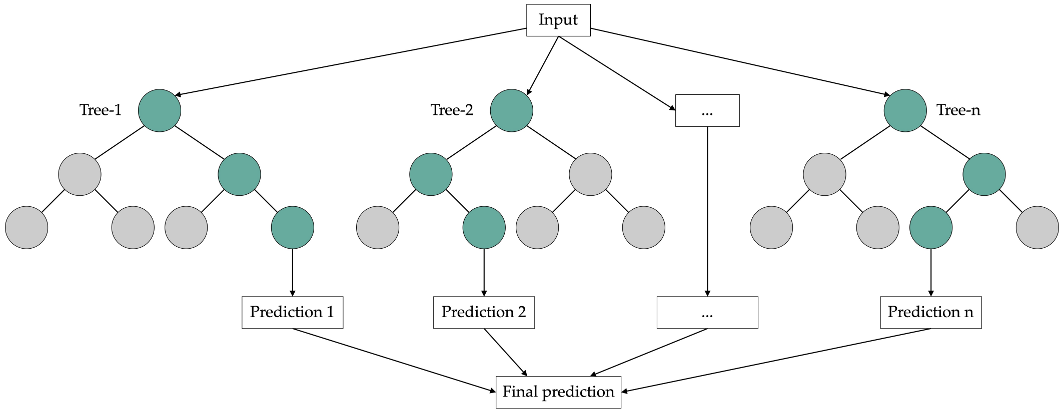


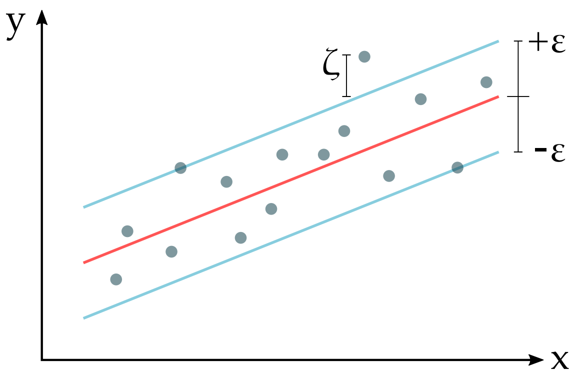

Image: Biljecki et al. (2016)

# Machine learning algorithms

1. Random Forest (RF)
2. Gradient Boosting (GB)
3. Suppor Vector Regression (SVR)




Random Forest




Linear SVR

# Implementation details

# Software & tools

## 1. Database

PostgreSQL

PostGIS

## 2. Processing

python™

pandas

scikit learn

## 3. Visualisation

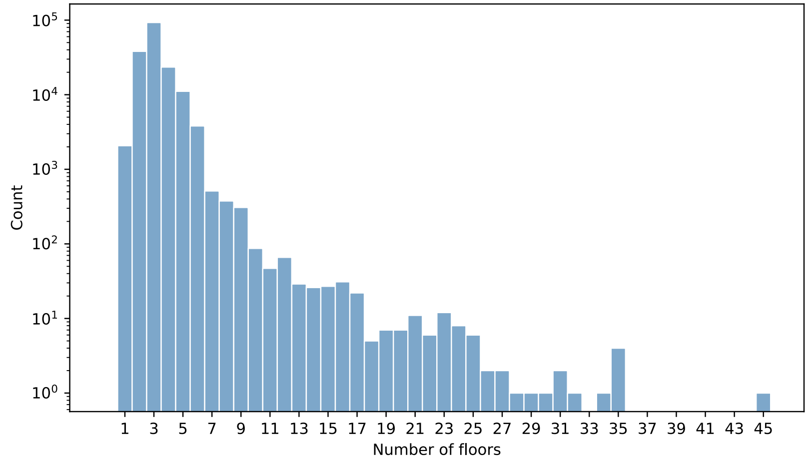
matplotlib

seaborn

# Datasets

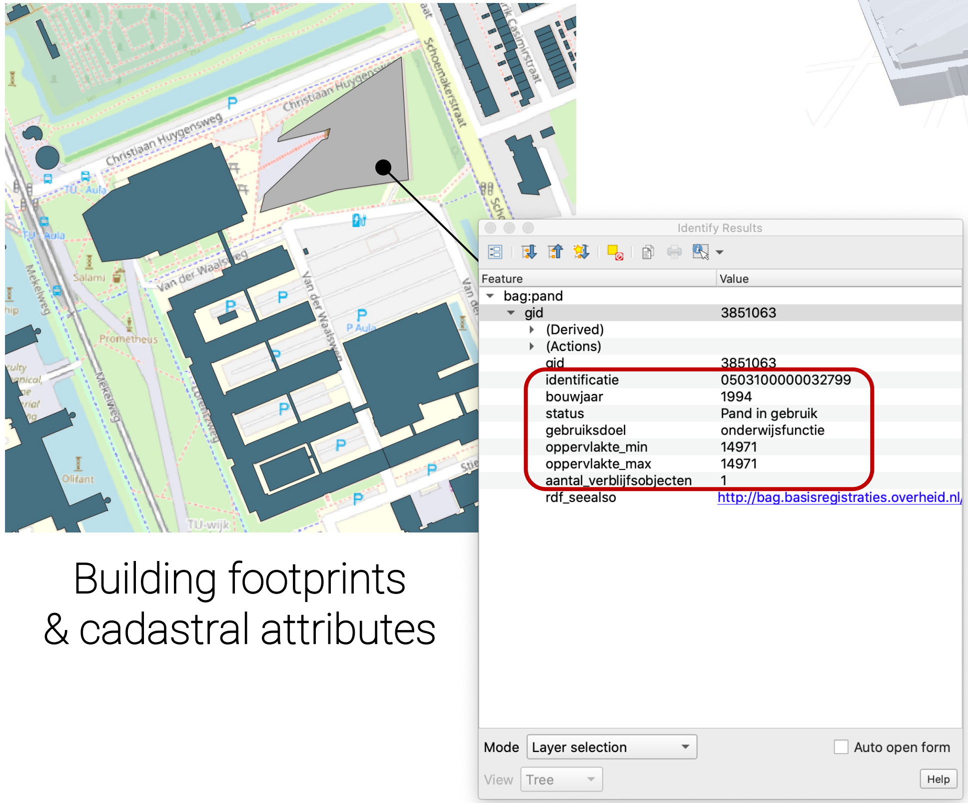
## Data on number of floors

| Municipality | # buildings |
|---|---|
| Amsterdam | 14,341 |
| Rotterdam | 116,638 |
| Den Haag | 53,559 |
| Rijssen-Holten | 11,516 |
| Total | 196,054 |

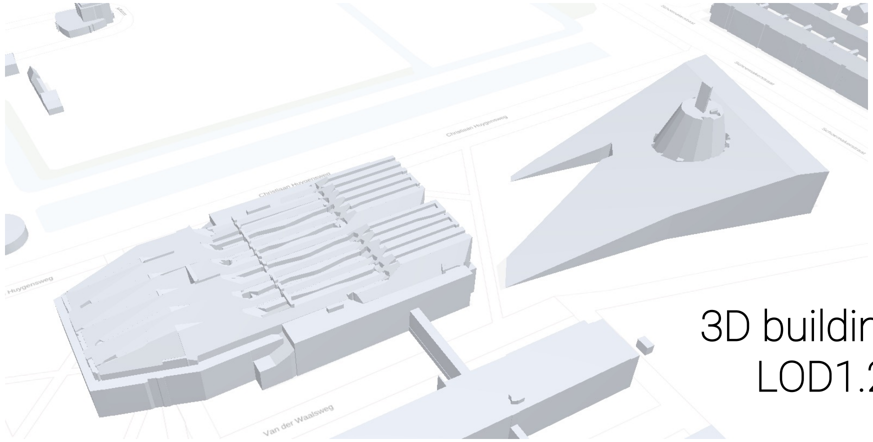
# Datasets

## BAG



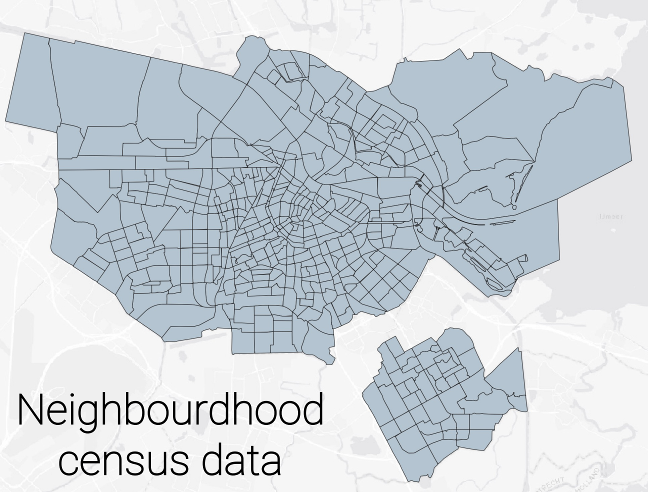

Building footprints
& cadastral attributes

## 3D BAG



3D building models in LOD1.2, 1.3, 2.2

## CBS wijken en buurten



Neighbourhood census data

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- Research objectives
- Background
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- **Implementation**
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# Data cleaning

Approximately **11%** of mixed-residential buildings removed

| Cleaning step | # buildings removed |
|---|---|
| Automatic | 11,383 |
| Semi-automatic | 11,394 |
| Manual | 27 |
| Total | 22,804 |

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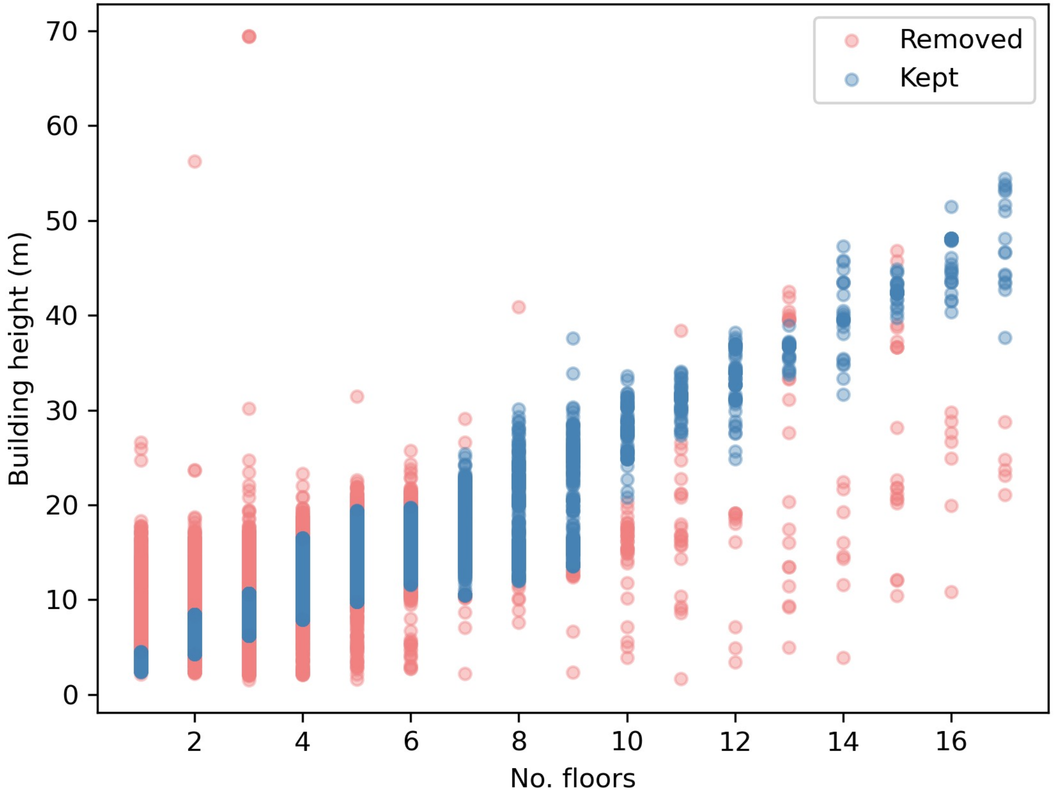
# Data cleaning




Actual: 4 floors
Training data: 2 floors

Actual: 5 floors
Training data: 2 floors

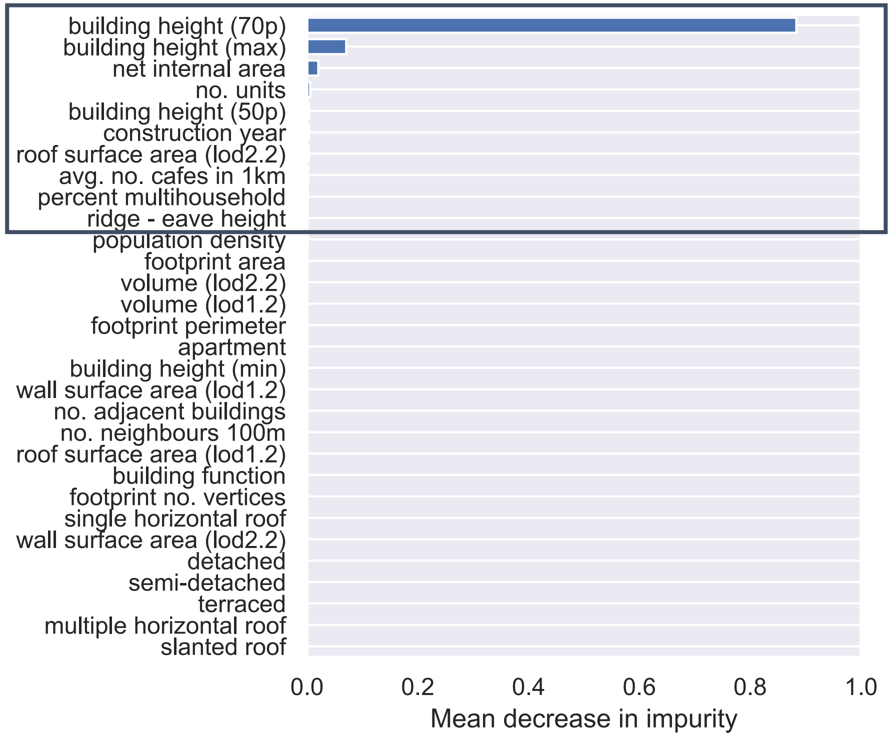
# Feature selection

## Method 1: Filter-based

| | Feature subset |
|---|---|
| 1 | Height (70th) |
| 2 | Height (max) |
| 3 | Height (50th) |
| 4 | Roof area (LOD1.2) |
| 5 | Roof area (LOD2.2) |
| 6 | Net internal area |
| 7 | Volume (LOD1.2) |
| 8 | Volume (LOD2.2) |
| 9 | Population density |
| 10 | % multihousehold |

## Method 2: Embedded

Feature importance GBR

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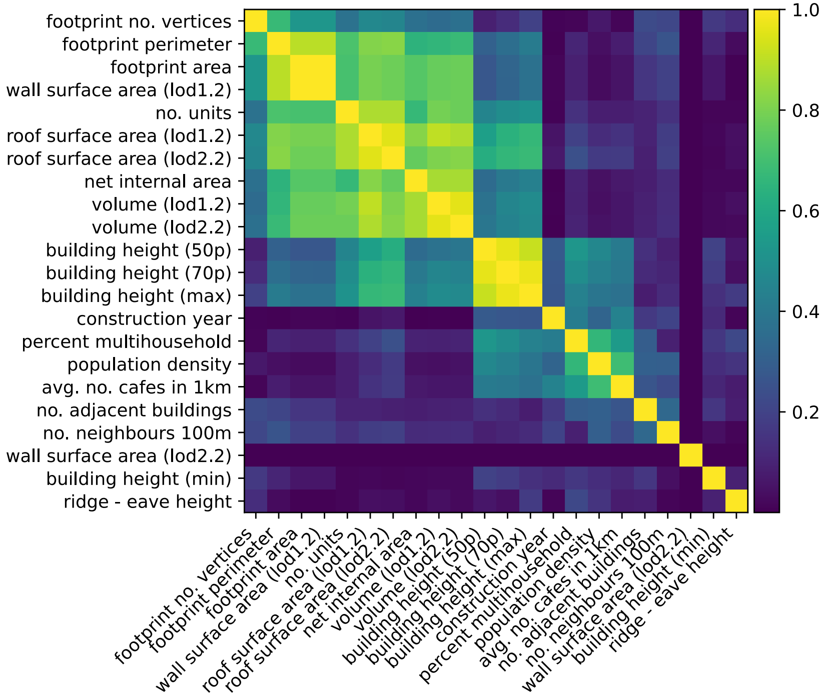
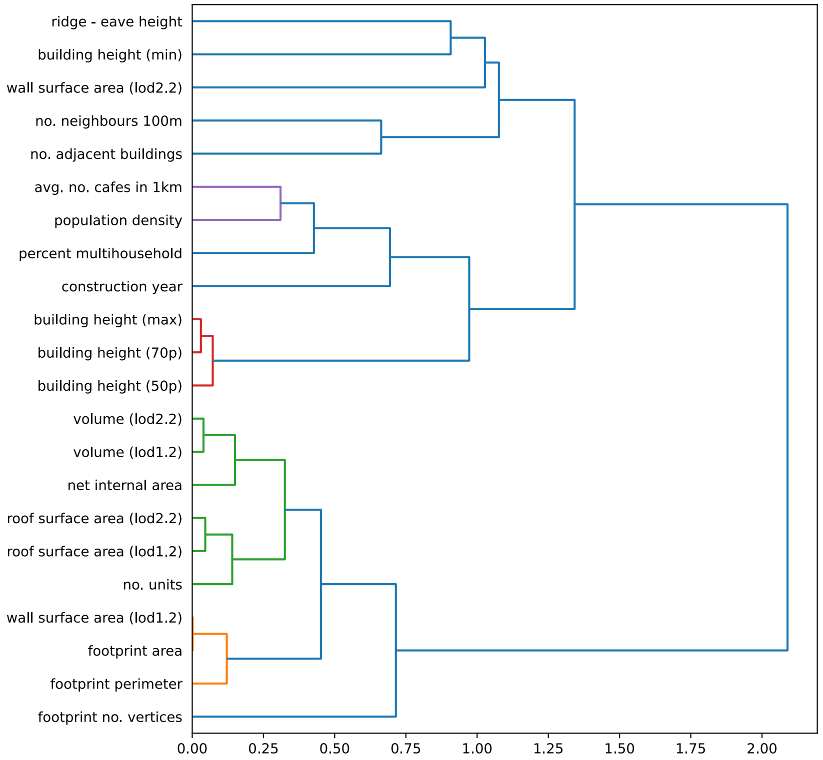
# Feature selection

- Method 3: Multicollinearity reduction




Pearson's correlation coefficient




Hierarchical clustering

# Results

# Model performance

## Gradient Boosting Regression (GBR)

| | MAE | | RMSE | | Max. error | | Accuracy (%) | | Training time (s) |
|---|---|---|---|---|---|---|---|---|---|
| | > 5 | ≤ 5 | > 5 | ≤ 5 | > 5 | ≤ 5 | > 5 | ≤ 5 | |
| All | 0.98 | 0.11 | 1.29 | 0.33 | 4 | 2 | 25.6 | 89.6 | 71.15 |
| Subset 1 | 1.04 | 0.11 | 1.36 | 0.33 | 5 | 2 | 24.1 | 89.4 | 40.71 |
| Subset 2 | 0.98 | 0.11 | 1.31 | 0.33 | 5 | 2 | 27.0 | 89.6 | 31.99 |
| Subset 3 | 1.02 | 0.12 | 1.33 | 0.35 | 4 | 2 | 23.7 | 88.4 | 35.08 |

MAE = Mean Absolute Error

RMSE = Root Mean Square Error

- Research objectives
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# Model performance

## Before and after hyperparameter tuning

| GBR subset 2 | MAE | | RMSE | | Max. error | | Accuracy | |
|---|---|---|---|---|---|---|---|---|
| | > 5 | ≤ 5 | > 5 | ≤ 5 | > 5 | ≤ 5 | > 5 | ≤ 5 |
| Untuned | 0.98 | 0.11 | 1.31 | 0.33 | 5 | 2 | 27.0 | 89.6 |
| Tuned | 0.62 | 0.06 | 1.00 | 0.24 | 4 | 3 | 52.3 | 94.5 |

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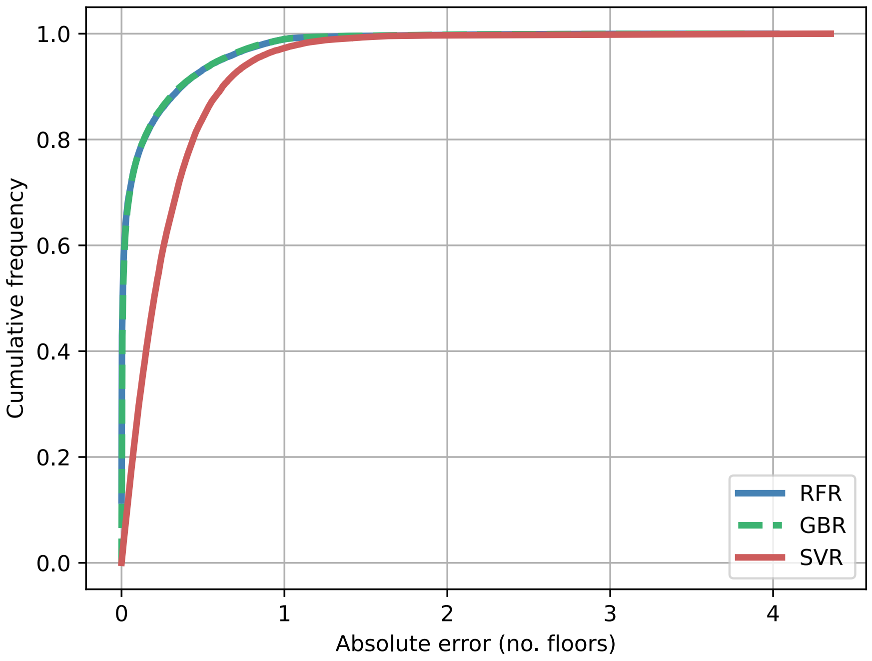
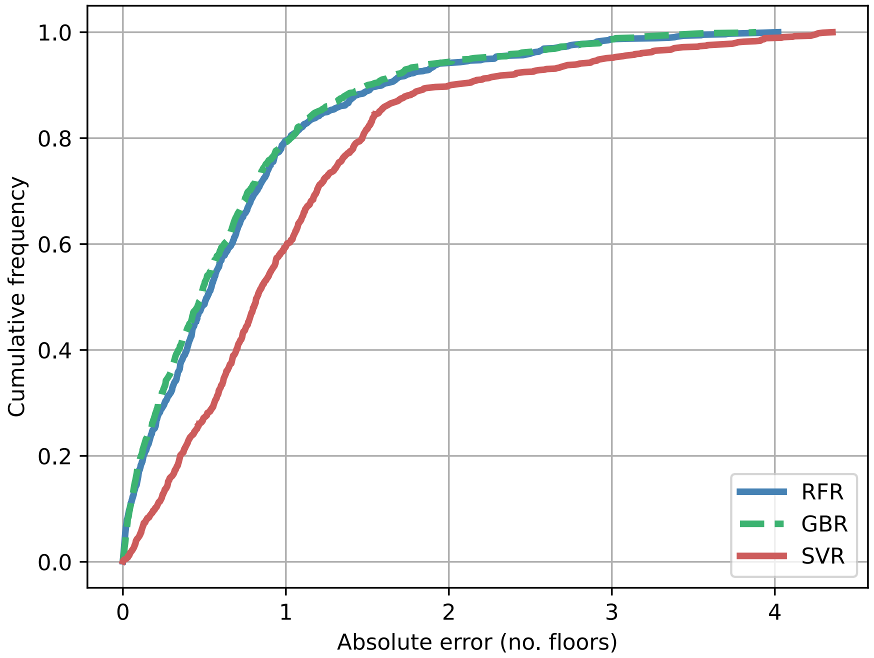
# Cumulative error analysis






All buildings




> 5 floors

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# Gross errors

Incorrectly labelled


Actual: 5 floors

Label: 9 floors

ML: 5 floors

Exceptionally tall storeys

Actual: 4 floors

Label: 4 floors

ML: 7 floors

High storey apartments

Actual: 14 floors

Label: 15 floors

ML: 17 floors

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# Comparison to geometric approach

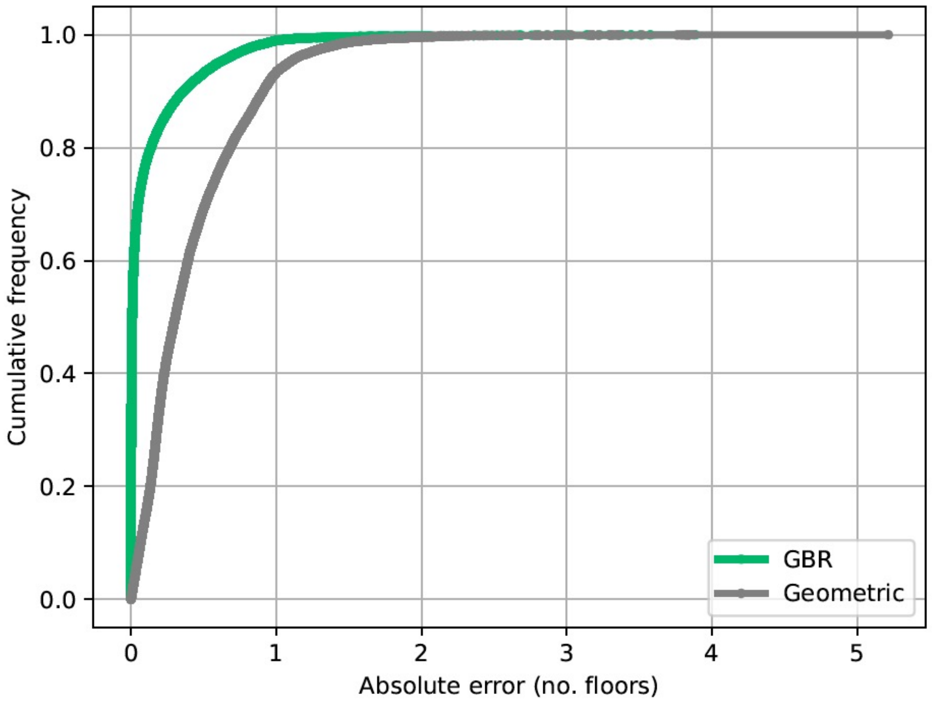
- Buildings with 5 floors or less

| | MAE | RMSE | Max. error | Accuracy (%) |
|---|---|---|---|---|
| GBR | 0.06 | 0.24 | 3 | 94.5 |
| Geometric | 0.31 | 0.31 | 2 | 69.9 |

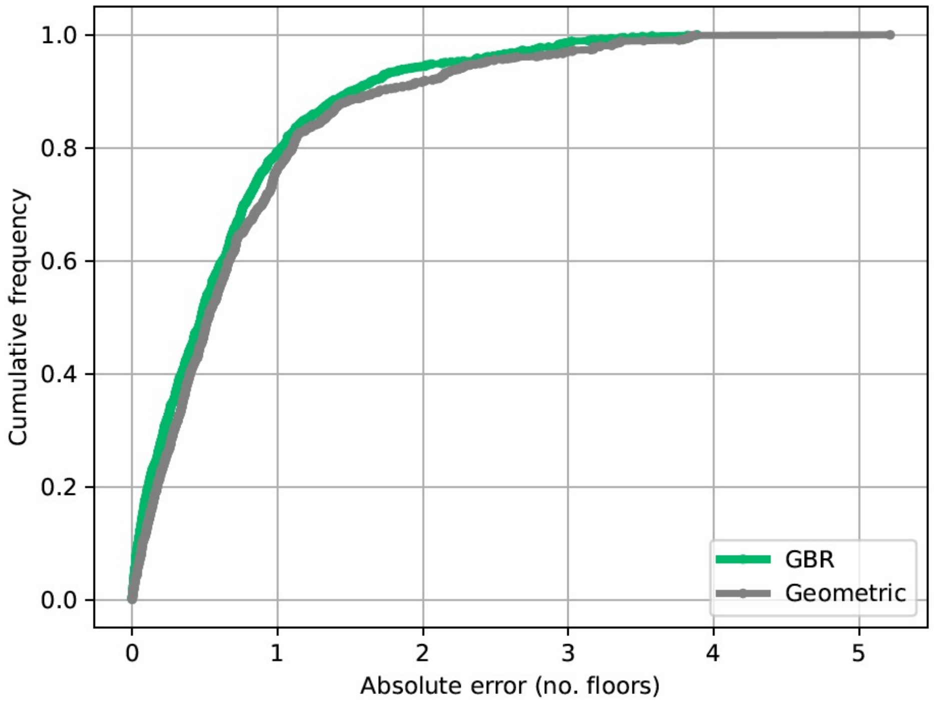
- Buildings above 5 floors

| | MAE | RMSE | Max. error | Accuracy (%) |
|---|---|---|---|---|
| GBR | 0.62 | 1.00 | 4 | 52.3 |
| Geometric | 0.70 | 1.09 | 5 | 47.5 |

# Comparison to geometric approach



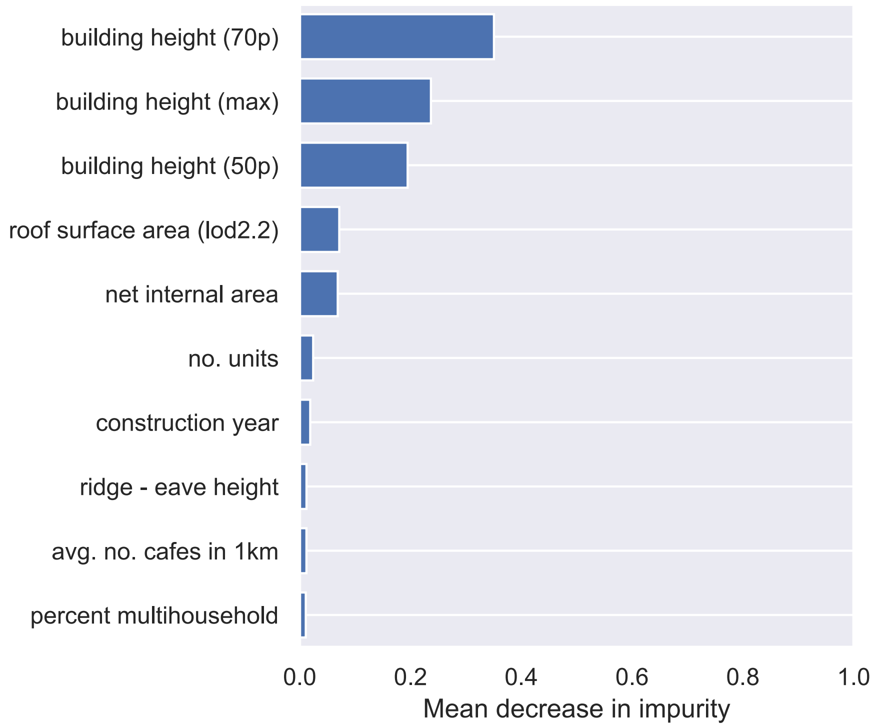

All buildings



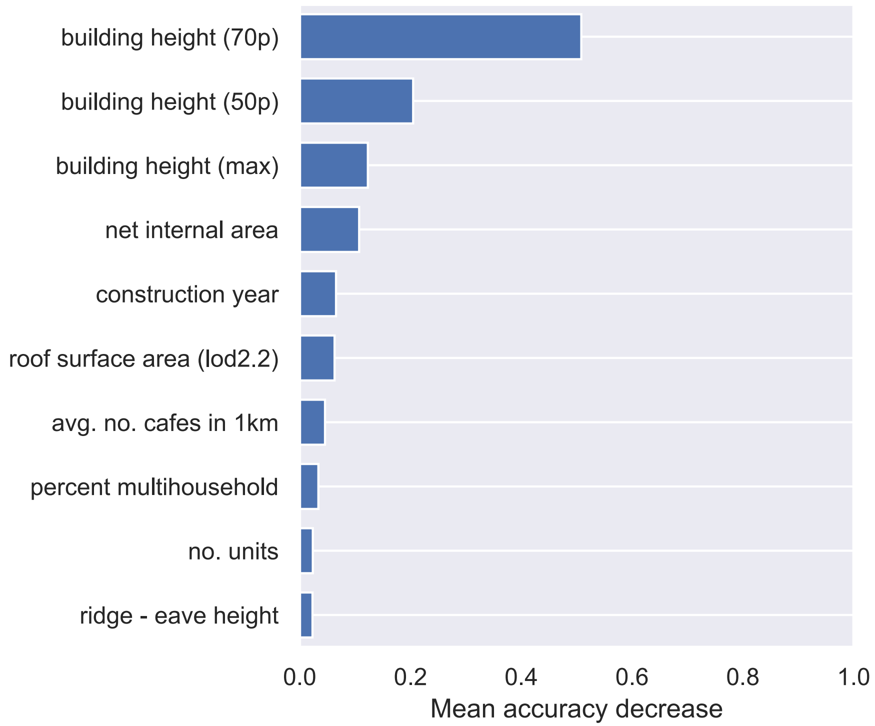

> 5 floors

# Feature contributions

- Research objectives
- Background
- Methodology
- Implementation
- **Results**
- Conclusions




Impurity importance




Permutation importance

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# Impact of data availability

| | | MAE | | Accuracy (%) | |
|---|---|---|---|---|---|
| | | > 5 | ≤ 5 | > 5 | ≤ 5 |
| All features | | 0.64 | 0.05 | 51.7 | 94.8 |
| Cadastral | | 1.35 | 0.19 | 25.3 | 82.5 |
| Geometric | 2D | 2.23 | 0.39 | 5.8 | 65.2 |
| | LOD1.2 | 0.89 | 0.10 | 32.5 | 90.1 |
| | LOD2.2 | 0.87 | 0.10 | 34.8 | 90.5 |
| Census | | 2.55 | 0.41 | 3.6 | 61.7 |
| | | | | | |
| Subset 2 | | 0.62 | 0.06 | 52.3 | 94.5 |

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# Conclusions

# Main research question

To what extent can **machine learning** provide a **better estimate** of the number of floors than a **purely geometric** approach?

Partially

| Low storey | High storey |
|---|---|
| Substantially better | Little improvement |

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# Sub-question (a) – features

- Most relevant feature: building height
- Other relevant features: volume, roof area, net internal area
- Overlaps: height references and 3D geometric features
- Best subset: unclear

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# Sub-question (b) – model results



- Best algorithm: Gradient Boosting
- Effect of data availability:
  - Best performance: 3D geometric features (LOD1.2 or LOD2.2)
  - Worst performance: 2D geometric and census features

# Sub-question (c) – comparison to geometric approach

- Research objectives
- Background
- Methodology
- Implementation
- Results
- **Conclusions**

- Buildings ≤ 5 floors: 25% higher accuracy
- Buildings > 5 floors: 5% higher accuracy
- Cumulative error distributions: comparable for errors ≥ 1 floor
- Gross errors: mainly incorrectly labelled buildings

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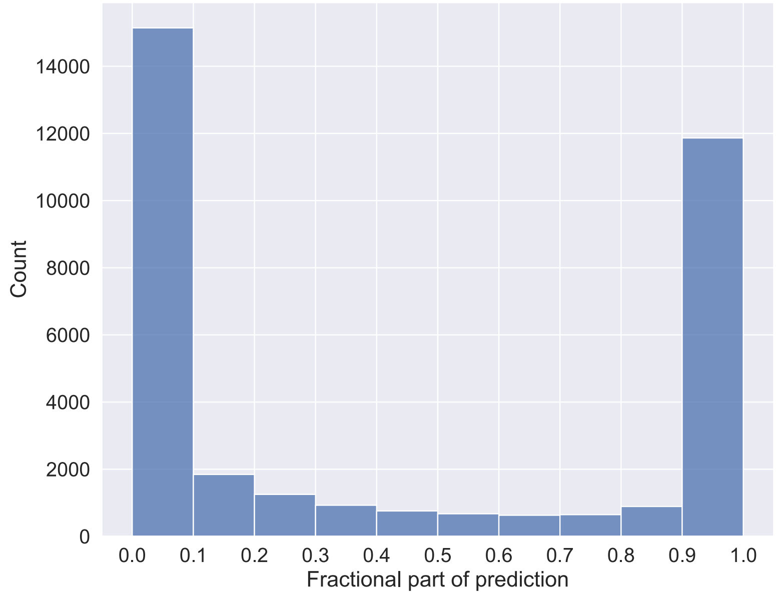
# Sub-question (d) – regression vs. classification

- Regression or classification? Regression
- Impact of rounding? Little impact on results

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# Contributions

- Reliability of geometric approach
- Analysis of contributing factors
- Regression vs. classification

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# Limitations

- Training data
- Data cleaning
- Feature selection
- Model performance and results

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- Research objectives
- Background
- Methodology
- Implementation
- Results
- Conclusions

# Future work

- Wider model applicability
- Automatic data correction
- Analysis of input features
- Improved geometric approach

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Thank you for your attention!

# References


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