Automatic change detection in digital maps using aerial images and point clouds

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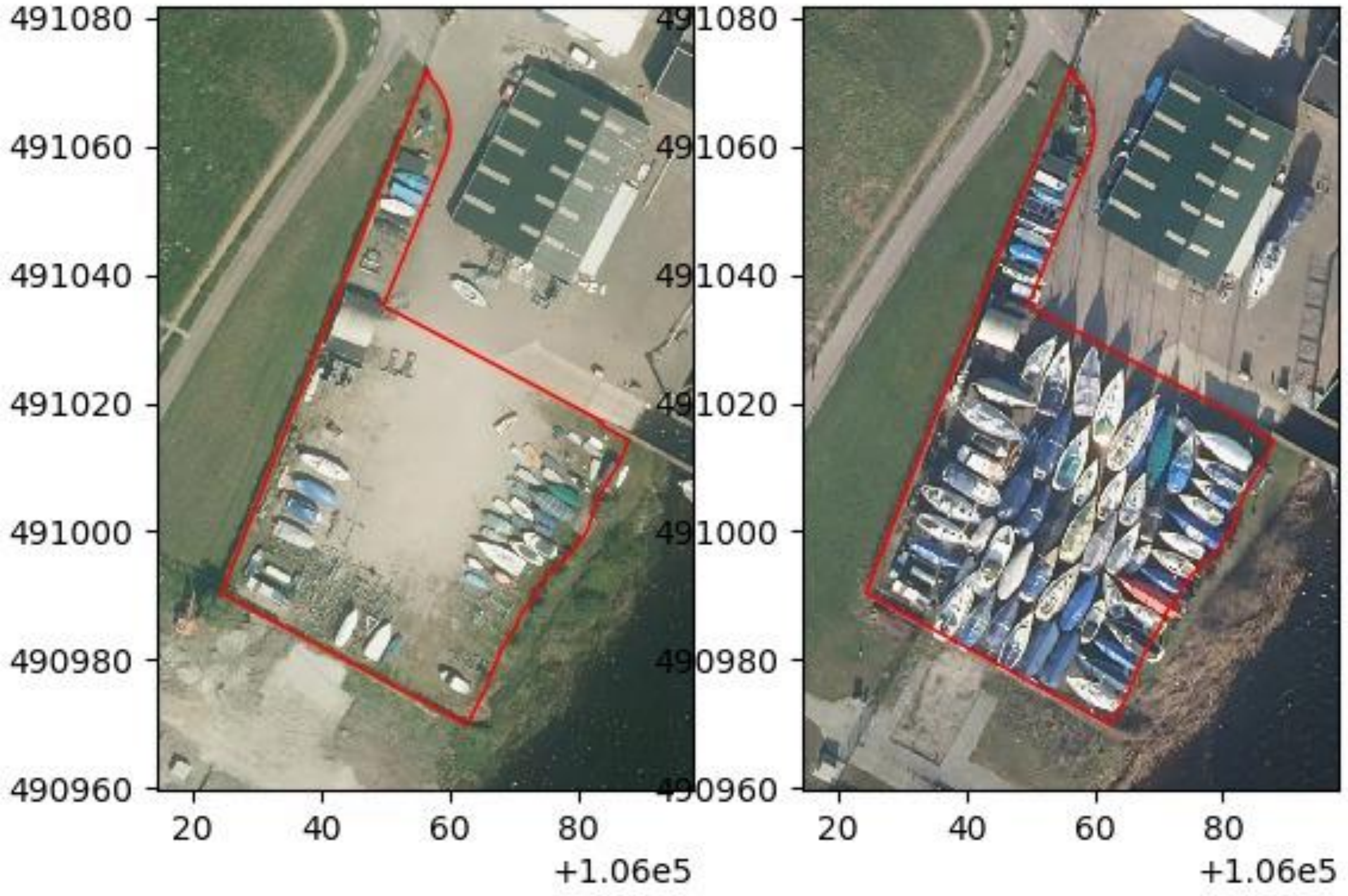

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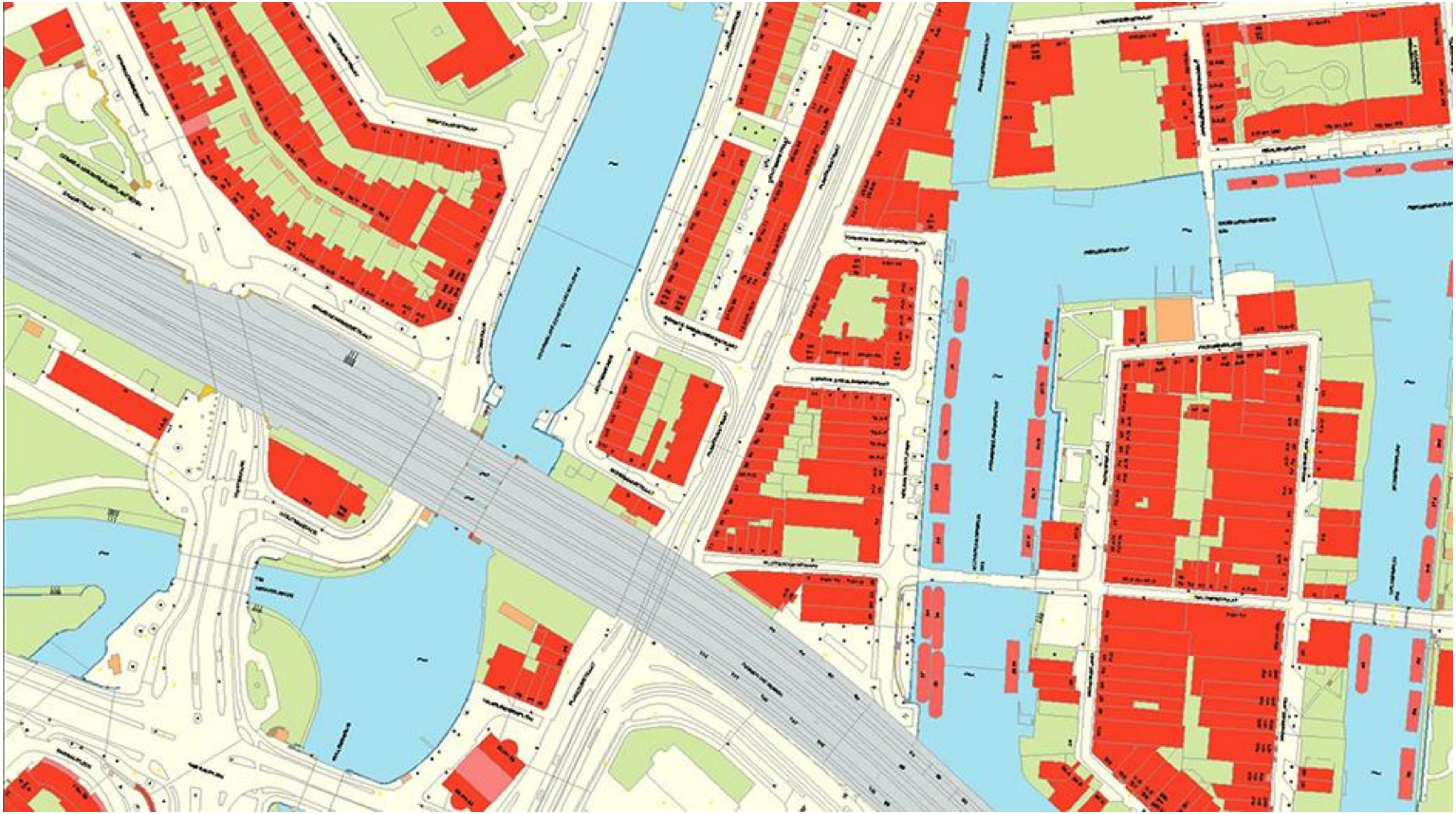
Digital maps must be updated regulary – still done by hand



Content

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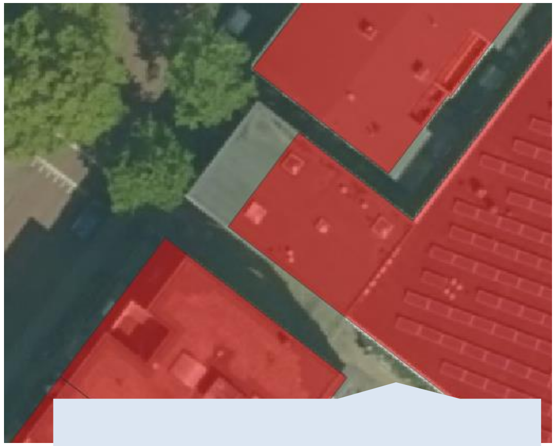
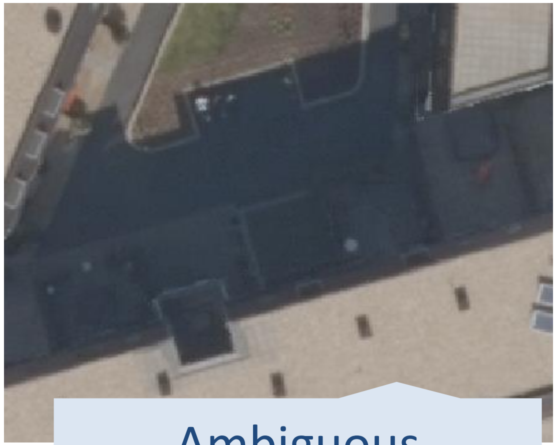
Introduction

Motivation



Human errors



Ambiguous situations

Many objects

- Susceptible for **errors**
- **Time consuming**

Solution is machine learning

Machine Learning can support this process through **automization of the change detection**

Input

- Aerial images & point clouds from consecutive years
- Digital map from current year

Output

- Which polygons are changing (probability per polygon)
- Support of the manual updating process

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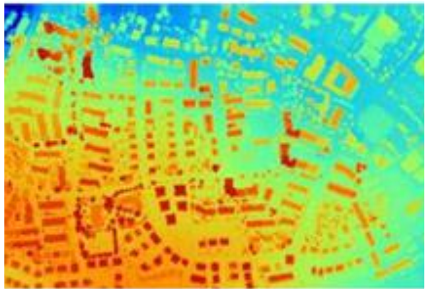
Data from various sources is used for one research area

Input data

Aerial images



Point cloud (DSM)

Digital maps

Research area

Research questions

To what extent can the change detection be automated using machine learning algorithms?

Which **features** of the input data can be used in terms of costs and benefits?

e. g:
- avg. red value
- category

Which **information** except height can be used from 3D point clouds?

e. g:
- slope
- aspect

Which **metrics** can be used to evaluate the results?

e. g:
- scores
- graphs

Is it possible to locate the **exact position** in which the change has happened?

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Related work

&

Background

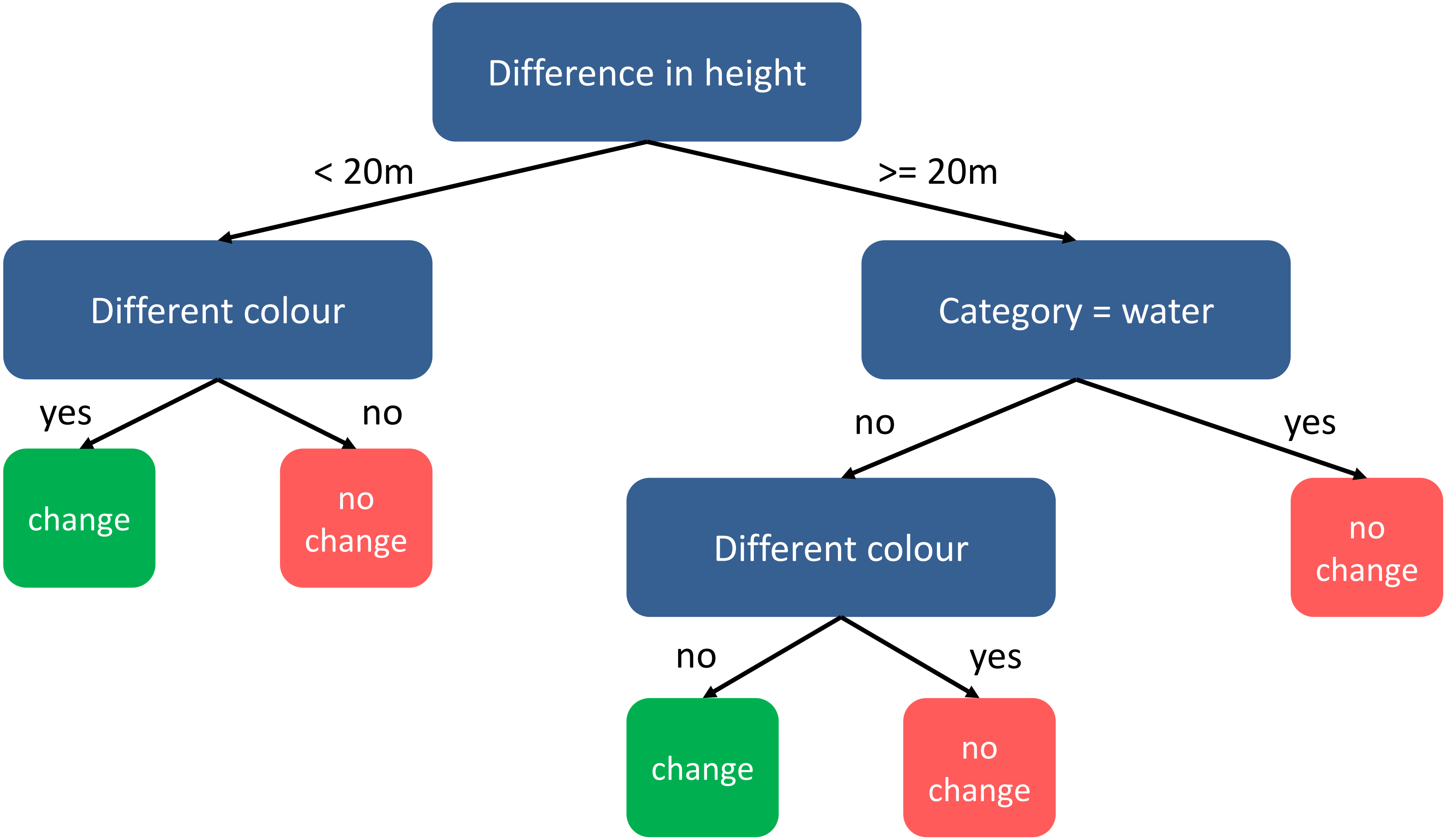
Insights from related research

Change detection used for many applications with **different techniques**: pixel-based → object-based → height included → machine learning

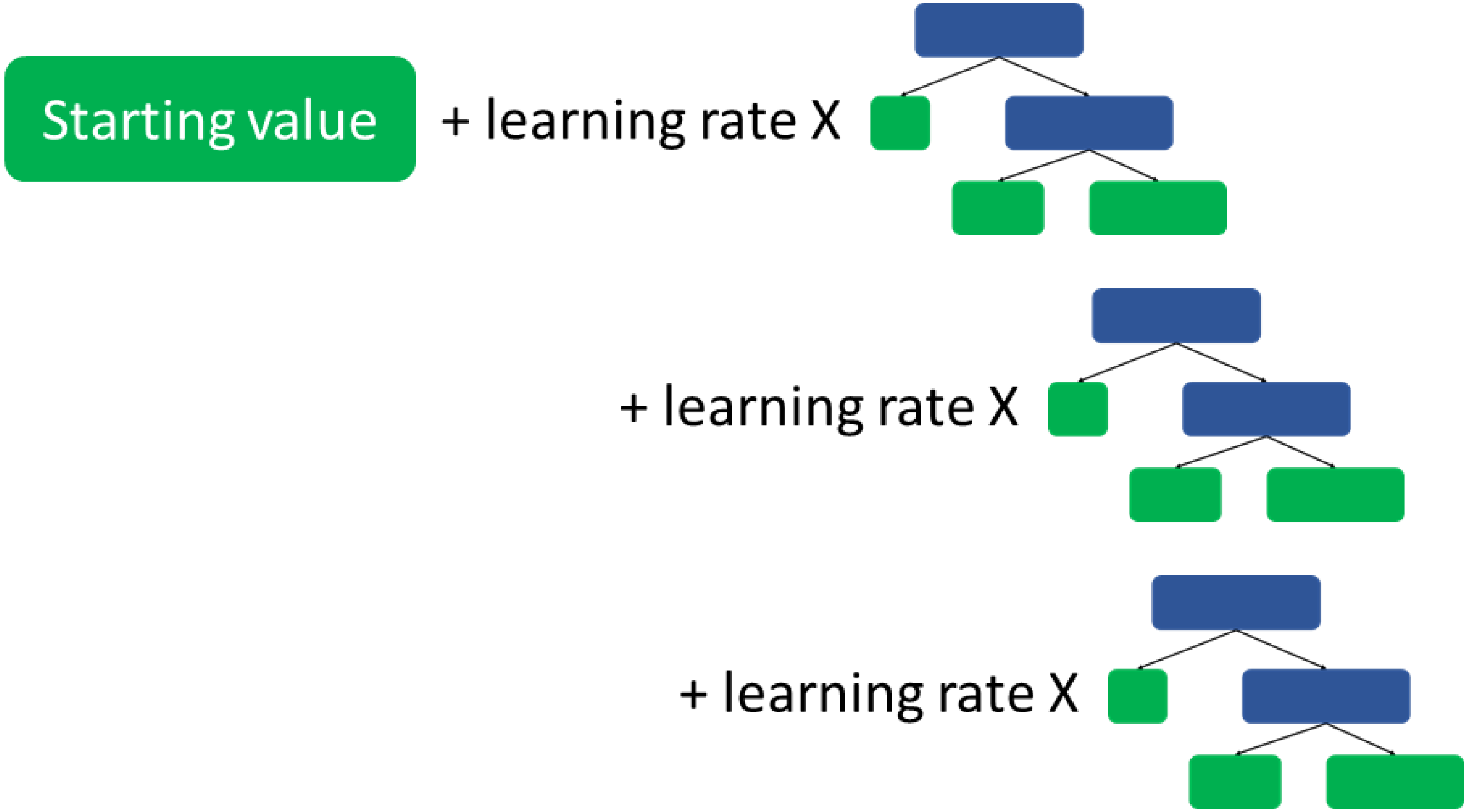
Holistic approaches are **rare**

For ML deep learning is used in most cases, **XGBoost is used less**

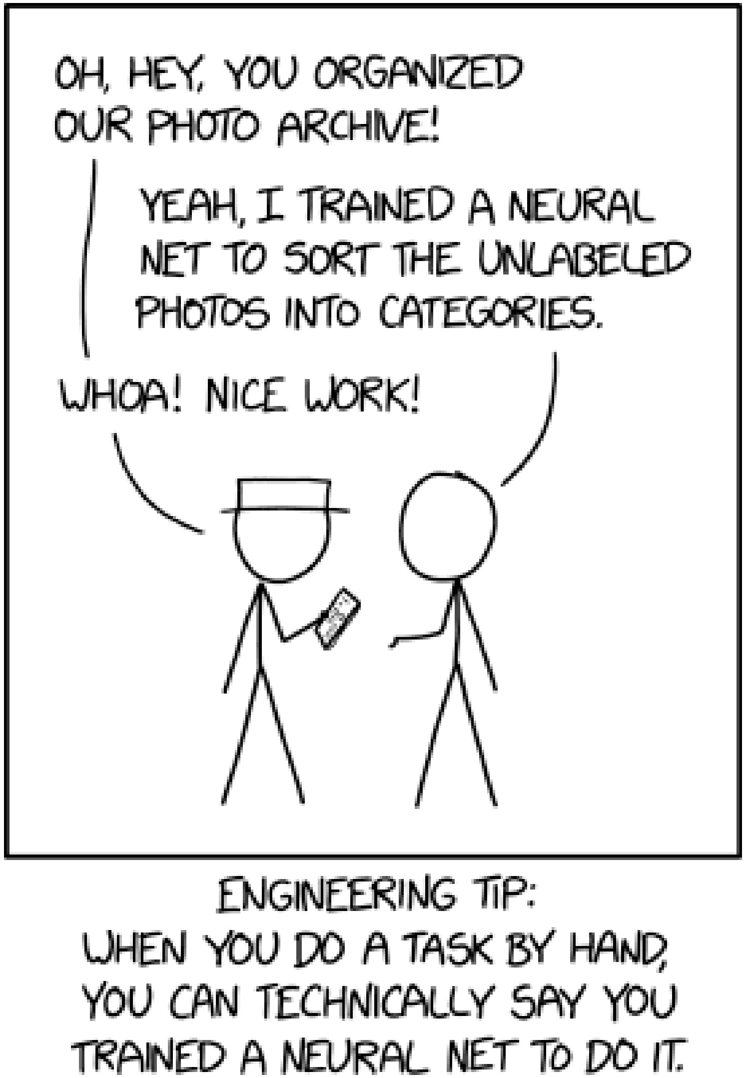
Decision trees help to classify based on many weak features



Gradient boosting combines multiple decision trees



Machine learning in a nutshell



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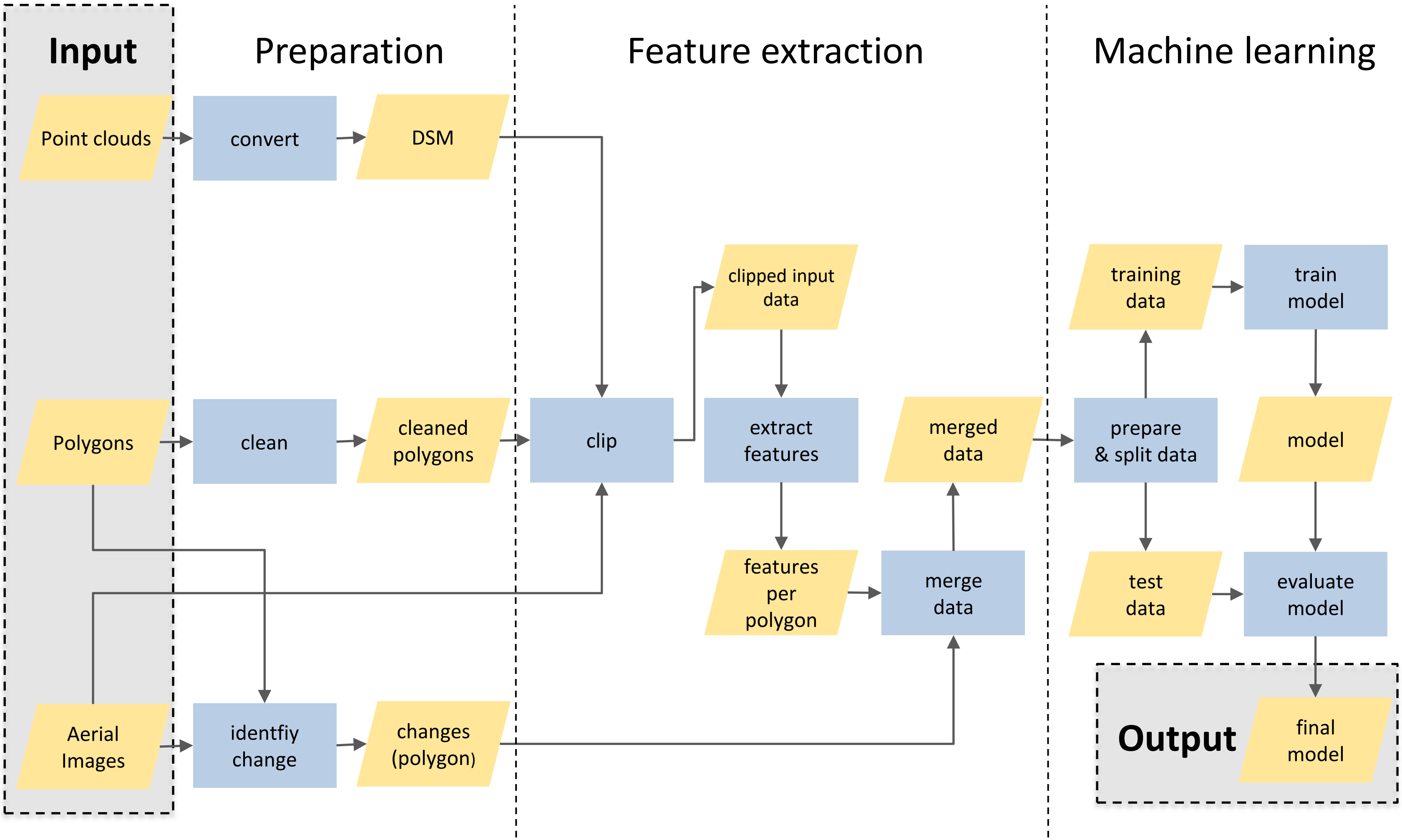
Methodology

Workflow can be divided in three big parts



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Features from different categories are used as input for XGBoost

Colour features

- Statistical values for RGB & HSV

Height features

- Statistical values for height & aspect & slope
- Number of pixels close to median height

Polygon features

- Category
- Shape of the polygon

Progressive features

- Shadow
- Bhattacharyya
- Haralick
- Fourier
- Local binary patterns

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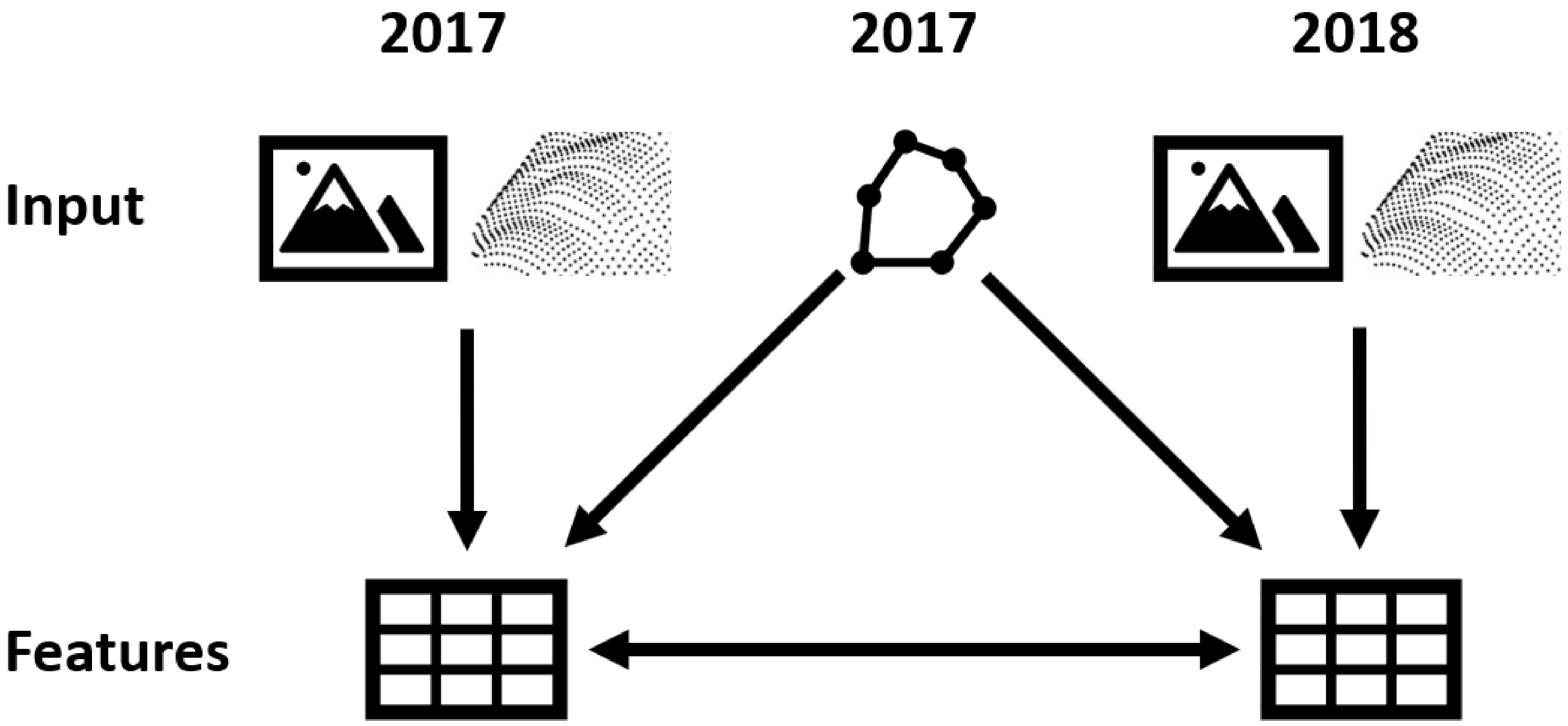
Features for both years are based on the polygons from 2017



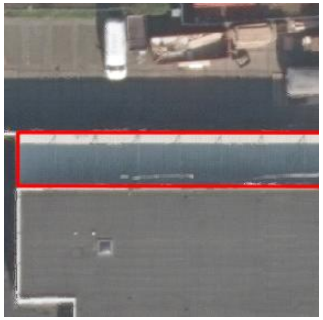
Implementation

For multiple BGT classes change detection is applied

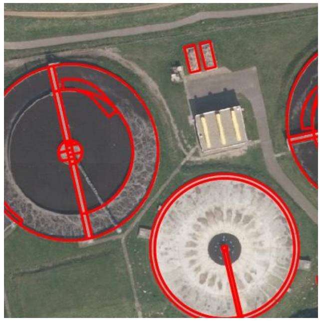
Pand

Wegdeel

Gebouwinstallatie



Overigbouwwerk



Waterdeel

Begroeidterreindeel

Onbegroeid-
terreindeel

Ondersteunend-
waterdeel

Ondersteunend-
wegdeel

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Features consist of numerical information

Colour Features

Feature	Value
red_min	103
red_max	154
red_avg	122.98
red_first_ percentile	106
red_last_ percentile	143
red_mode	124
red_std	8.63

Height Features

Feature	Value
height_ avg	29.774
height_ first_perc	24.252
height_ last_perc	31.579
slope_avg	14.171
aspect	159.691
npix_ height	0.825

Polygon Features

Feature	Value
n_pixels	630
length_x	6.4
length_y	3.5
compact ness	0.702
n_vertices	5
Category	Building*

*will be converted to a number

Progressive Features

Feature	Value
shadow_ percentage	7.04
haralick_ contrast	167.902
haralick_ Entropy	87.730
Peaks	0.7880
LBP[1]**	0
LBP[4]	7

** the number corresponds to the position at the histogram

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High number of objects with only a small percentage of changes

161,762 objects

1,378 changes

0.85 % changes

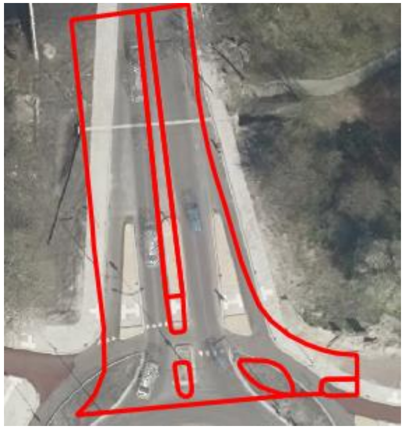
Results

Many changes could be classified correctly

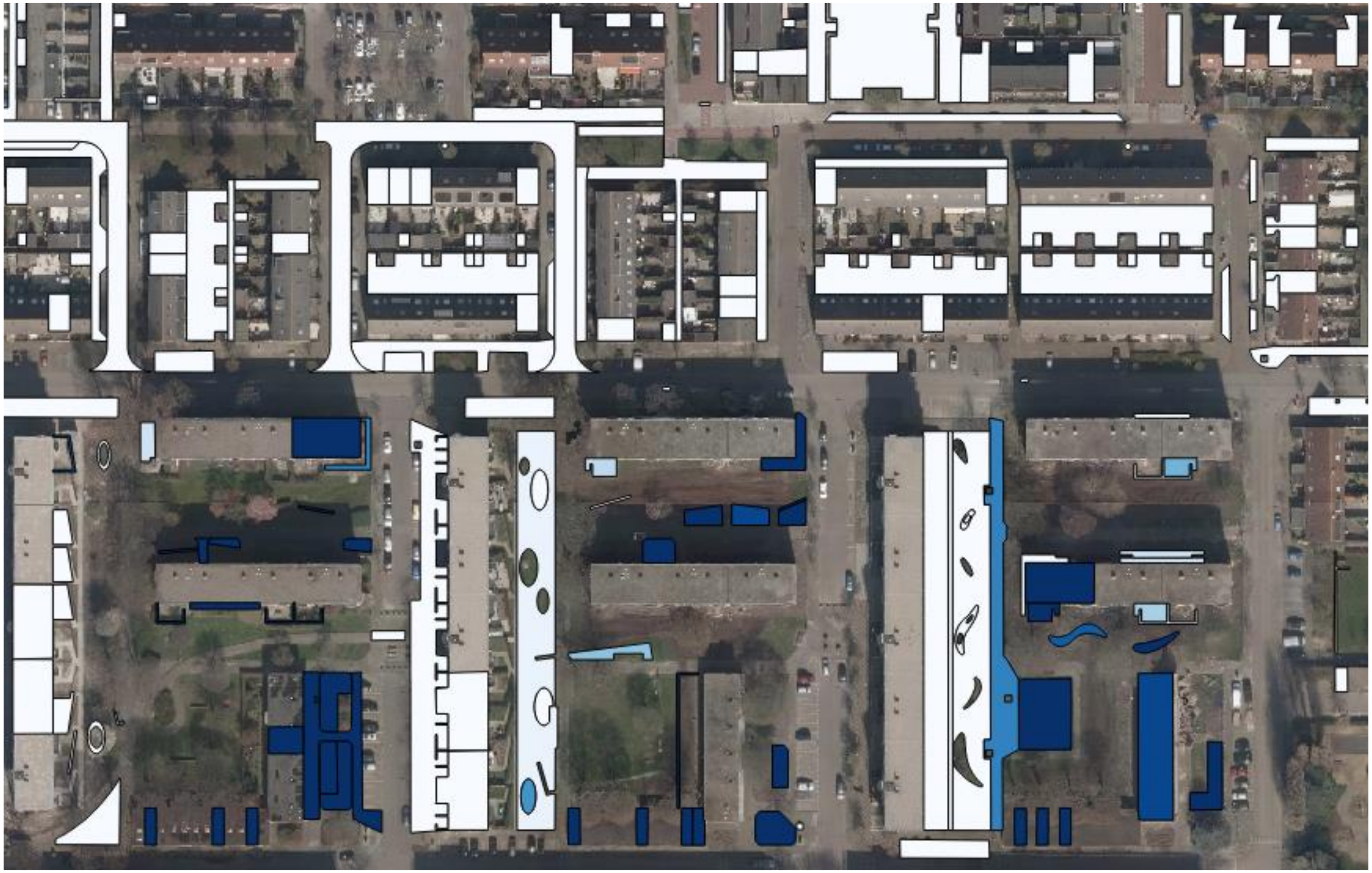






The outcome of my model

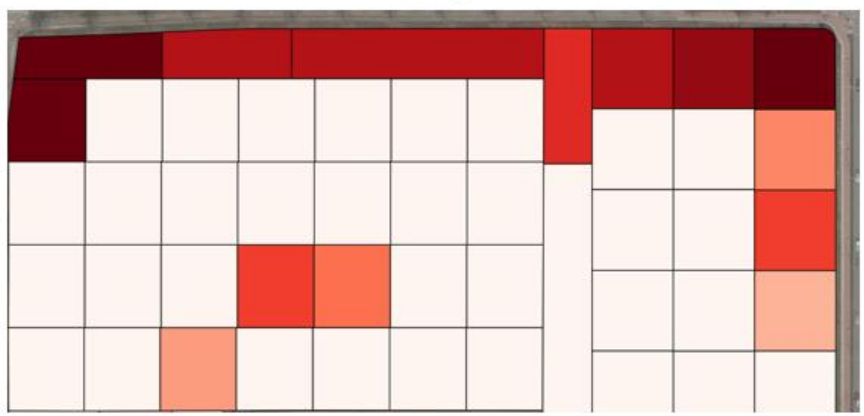


Locate changes via splitting polygons is successful

2017

2018

change



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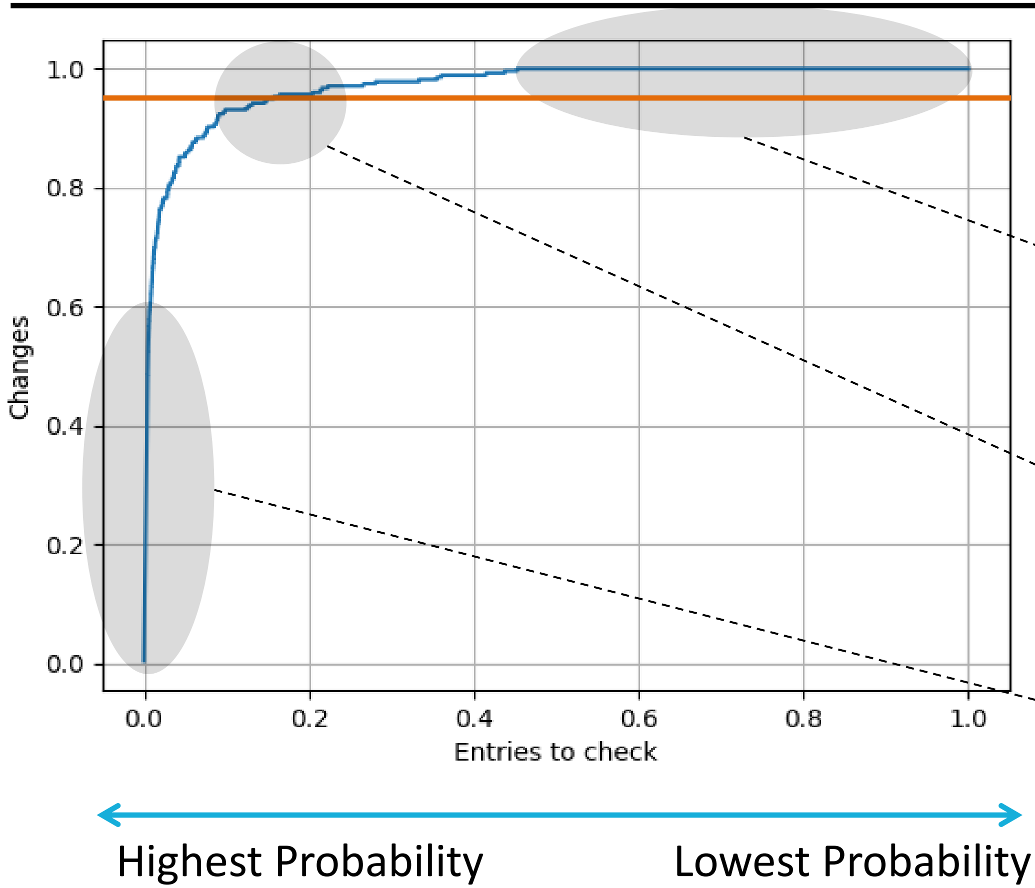
Confusion Matrix can provide insights for the exact numbers

		Real	
		Positive	Negative
Predicted	True	254	30,248
	False	1.761	22

Size test-set: 32.385 Threshold = 0.001

The economic curve displays the value for the customer

Economic curve



- On an economic scale the results are more satisfactory
- To find **all changes**, around **50%** of all entries must be checked
- To find **95%** of all changes around **15%** of all entries must be checked
- Around **60%** of all changes can be found with **highest probability**

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Discussion

Discussion

Change detection

- Best detection rate for buildings
- Mixed classes decrease detection rate
- More difficult for streets

Contributions

- Implemented a holistic change detection
- Used XGBoost for change detection
- Support for maintaining BGT
- Dealed with temporary changes

Future research

- Create features from deep learning
- Create a public test-set
- More training data needed

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Research questions could be answered successfully

To what extent can the change detection be automated using machine learning algorithms?

- Change detection is possible using XGBoost
- Suitable as a tool to set focus on certain areas
- Manual checking still required

Which **features?**

- More features » more refinement
- Height & category most contribution

Which **height information?**

- Spikes are a problem » no min/max values
- Not many features needed

Which **metrics?**

- Confusion matrix for representation
- PR-Curve for evaluation
- Economic curve for business

Exact position?

- Possible to localize
- No reconstruction of change

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THIS IS YOUR MACHINE LEARNING SYSTEM?
YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.
WHAT IF THE ANSWERS ARE WRONG?
JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.
DATA
ANSWERS