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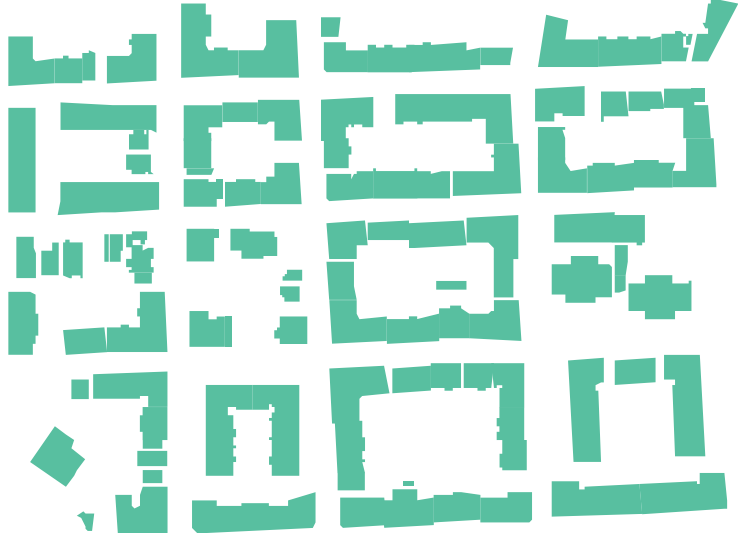
# URBAN MORPHOLOGY ENERGY NEEDS AND ARTIFICIAL INTELLIGENCE

ARTIFICIAL INTELLIGENCE AND ENERGY SYMPOSIUM

MARTIGNY, 07 MAY 2019

# WHAT?

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# WHY?

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## OPTIMIZATION

More precise models lead to more conscious choices from planners and designers, which in turn can result in an optimization of the energy use in their projects. This is especially important as it can help reducing greenhouse gas emissions.



## COMPLEXITY

The complexity of the problem and the underlying uncertainties forces models to provide a good trade-off between precision and execution time, to the point that phenomena like heat islands and urban canyons are often neglected.



## LACK OF DATA

When working at urban scale, the available data usually lacks some building-scale details and information. The assumptions made to fill these gaps can lead to a significant error in the final result.

# HOW?



The case study, as long as a training set with known outputs, must be provided as inputs.

## PREPARE DATA

The input data is cleaned and meaningful features are extracted from it.

Multiple algorithms are tested in order to find the best one for the specific case study.

## SELECT MODEL

## TRAIN MODEL

The chosen model is trained with the whole training dataset.

The estimation is finally made on the case study and the output results are stored in a table.

## OUTPUT

## INPUT

**INPUT**

PREPARE  
DATA

SELECT  
MODEL

TRAIN  
MODEL

**OUTPUT**



**TRAINING SET**

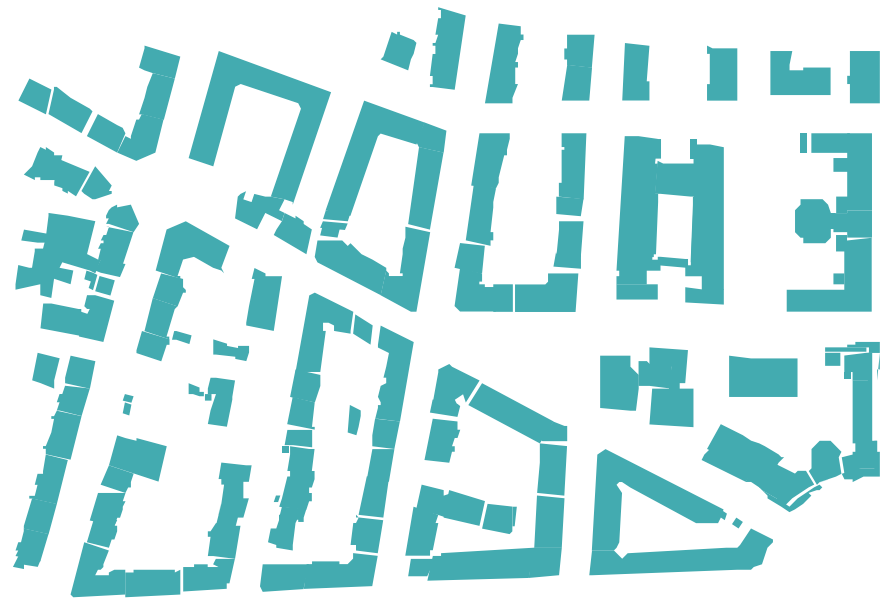
+



**PREDICTION SET**

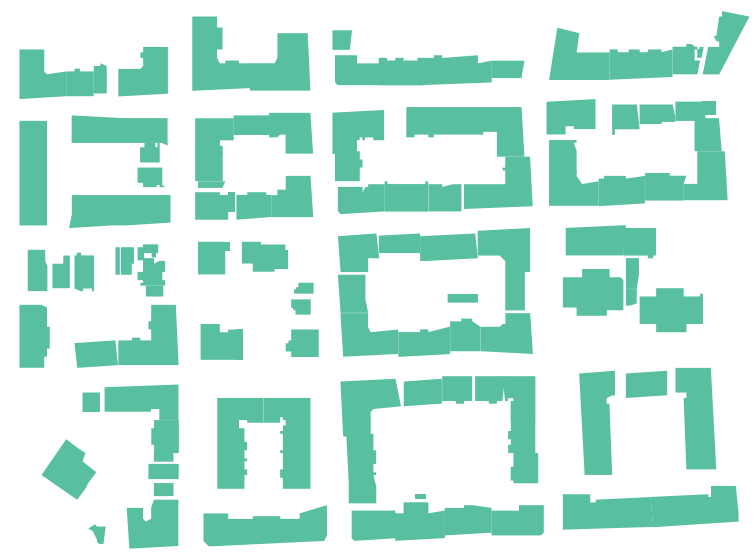
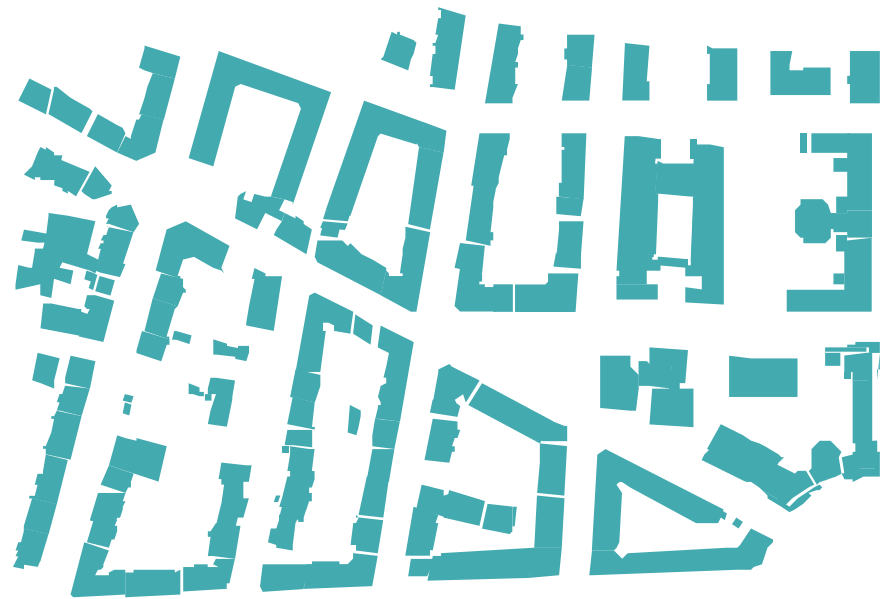
geometry	type	year	height	floors
LSMRI10...	1	1970	12	4
AHC39LS...	4	1935	6	2
KDF87L9...	3	2005	24	8
...				

INPUT  
PREPARE DATA  
SELECT MODEL  
TRAIN MODEL  
OUTPUT





INPUT  
PREPARE DATA  
SELECT MODEL  
TRAIN MODEL  
OUTPUT



**INPUT**

**PREPARE  
DATA**

**SELECT  
MODEL**

**TRAIN  
MODEL**

**OUTPUT**



### **BUILDING SCALE**

- Perimeter
- Footprint area
- Gross volume
- Number of people
- External surface
- Form factor
- Aspect
- Orientation
- Ventilation
- Glazing ratio
- U value
- Bound ratio



### **NEIGHBORHOOD SCALE**

- Shadowed portion 0
- Shadowed portion 1
- Shadowed portion 2

...



### **URBAN SCALE**

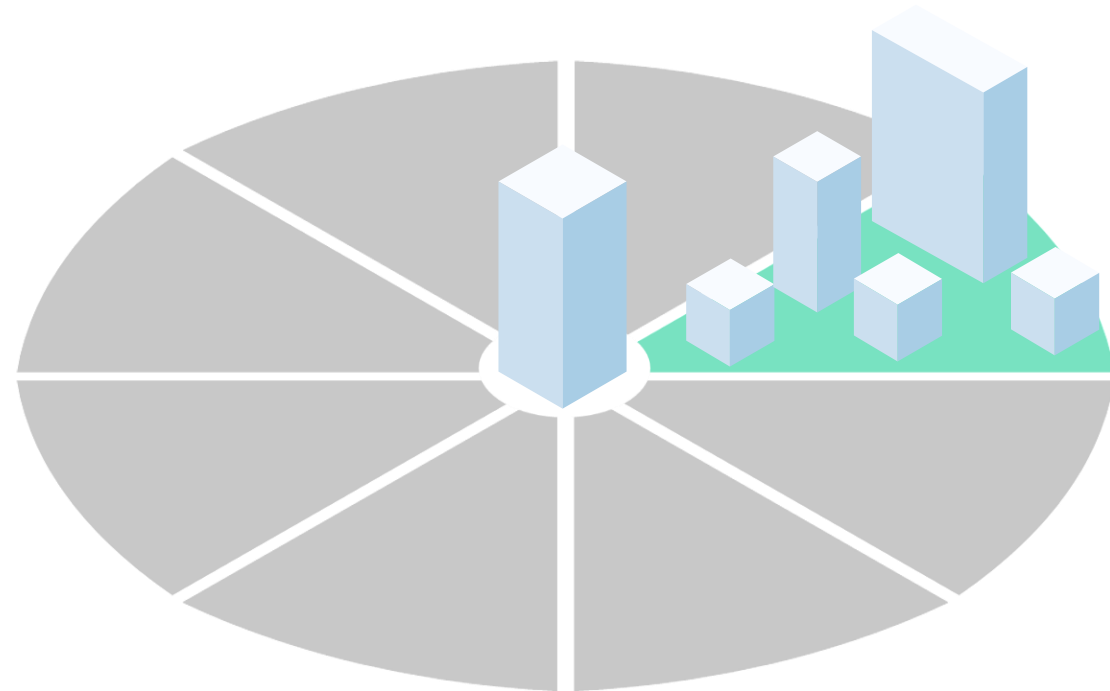
- Built coverage ratio
- Average building height
- Building aspect ratio



# NEIGHBORHOOD SCALE

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$$sp_i = \text{atan}\left(\frac{h_i}{d}\right) \cdot \min\left(\frac{h_i}{h}, 1.1\right)$$

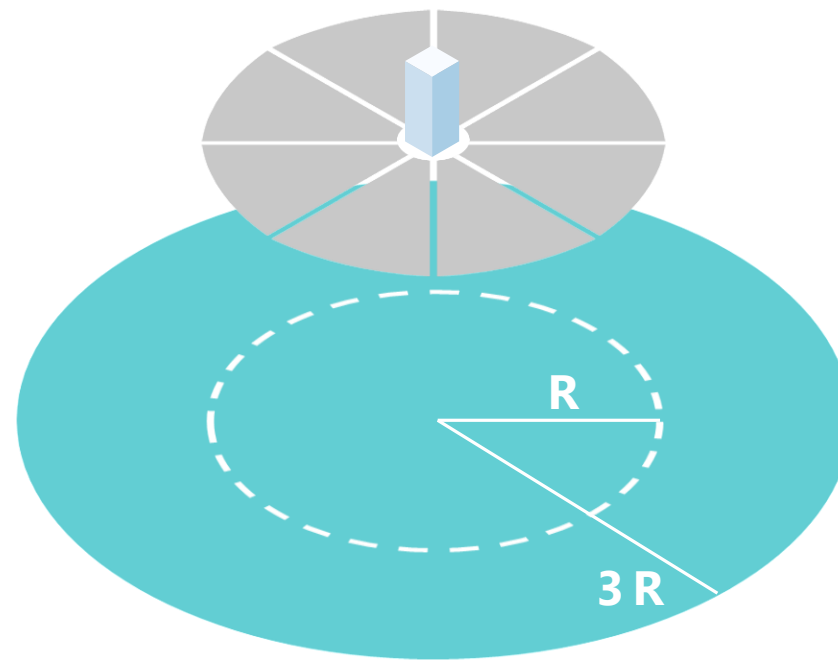


INPUT  
PREPARE  
DATA  
SELECT  
MODEL  
TRAIN  
MODEL  
OUTPUT

INPUT  
PREPARE  
DATA  
SELECT  
MODEL  
TRAIN  
MODEL  
OUTPUT

## URBAN SCALE

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**Built Coverage Ratio (BCR):** the proportion of the urban area that is occupied by buildings.

**Aspect Ratio (AR):** the ratio between the height of the building and the mean width of roads.

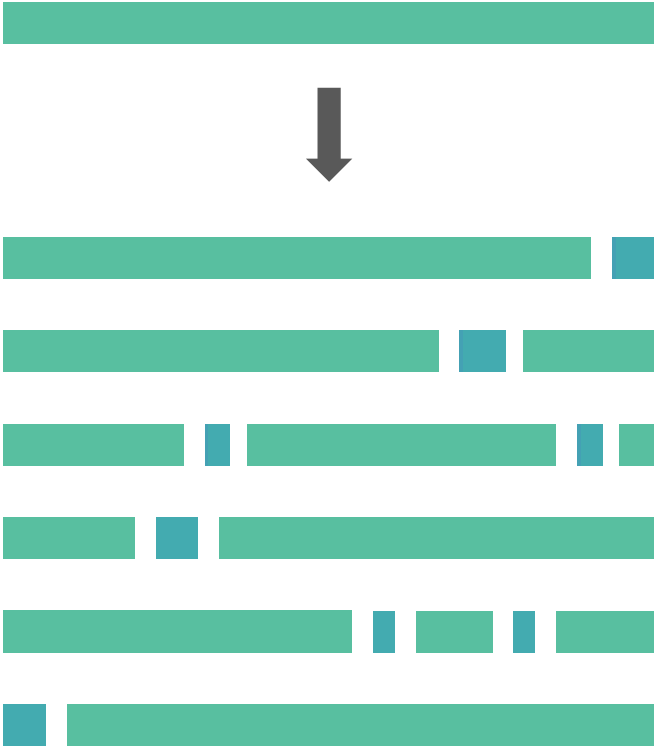
**Average Buildings Height (ABH):** the average height of the buildings in the urban area.

# SHUFFLE SPLIT

INPUT  
PREPARE DATA  
SELECT MODEL  
TRAIN MODEL  
OUTPUT

TRAINING SET

PREDICTION SET



The training set is randomly divided multiple times into a training and a testing subsets. The accuracy of each algorithm is evaluated for every subset, and the model which scores the best results is finally chosen.

# LEARNING...

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INPUT

PREPARE  
DATA

SELECT  
MODEL

TRAIN  
MODEL

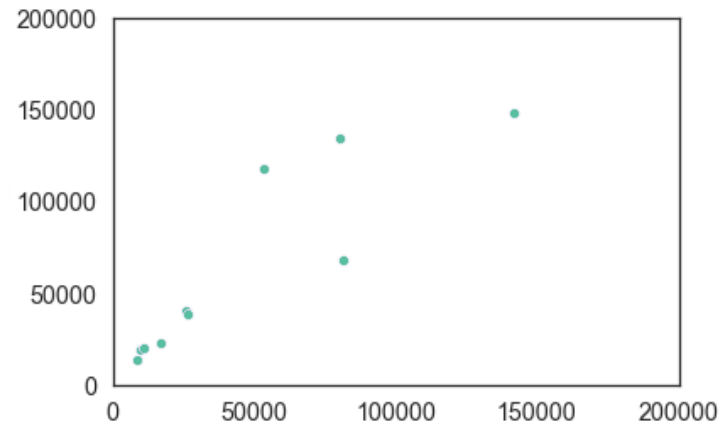
OUTPUT

# BROC

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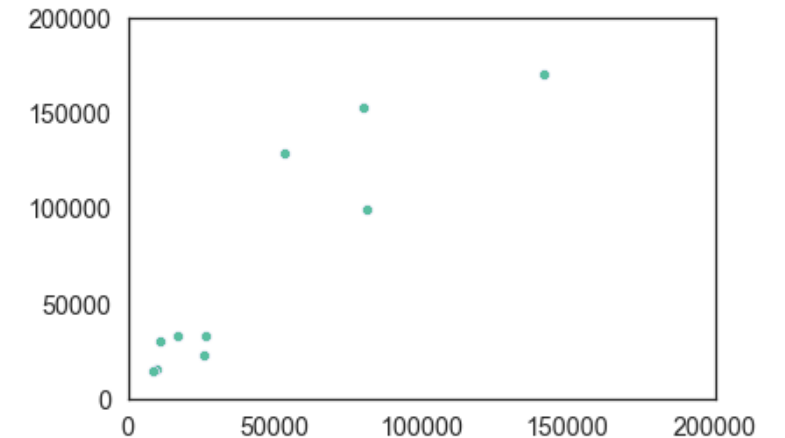
INPUT  
PREPARE  
DATA  
SELECT  
MODEL  
TRAIN  
MODEL  
OUTPUT

## ARTIFICIAL INTELLIGENCE



Mean error: 59.71%  
Median error: 60.25%  
Max error: 121.86%

## PHYSICS-BASED MODEL



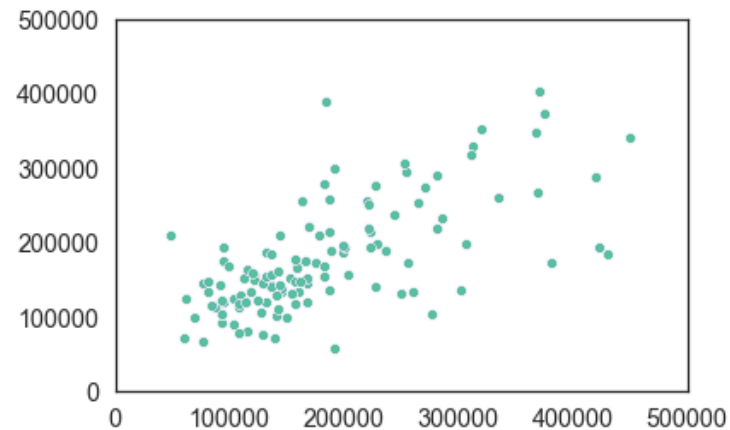
Mean error: 71.01%  
Median error: 65.85%  
Max error: 170.88%

# TURIN

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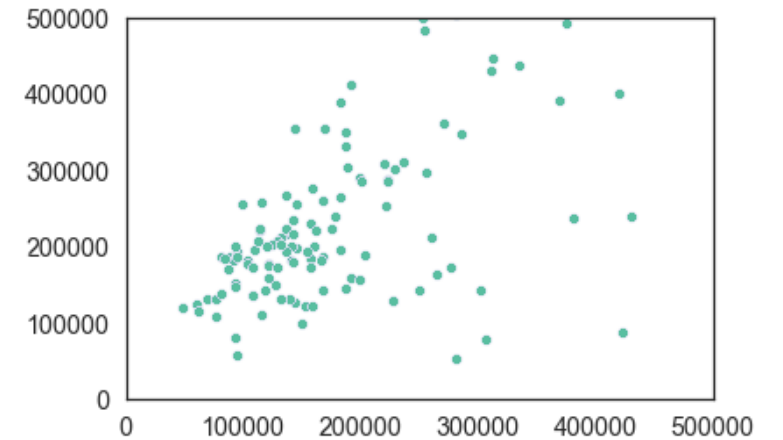
INPUT  
PREPARE  
DATA  
SELECT  
MODEL  
TRAIN  
MODEL  
OUTPUT

## ARTIFICIAL INTELLIGENCE



Mean error: 29.78%  
Median error: 20.99%  
Max error: 331.84%

## PHYSICS-BASED MODEL



Mean error: 58.89%  
Median error: 44.54%  
Max error: 371.85%

# POSSIBLE REASONS

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- Lack of details in urban-scale data led to wrong assumptions
- Physical-based software was not tuned with real consumption data
- Models might not grasp some regional differences, for example, in user behavior



# CONTEXT INFLUENCE

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- Factoring urban morphology has improved the precision by 1-7%
- The improvement especially affected the buildings where the error was high
- The Broc case study did not benefit much from them, probably because of the lack of data points

**THANK YOU!**



