URBAN MORPHOLOGY
ENERGY NEEDS
AND
ARTIFICIAL INTELLIGENCE
WHAT?
WHY?

**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.
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.

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.

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

### PREPARE DATA

### SELECT MODEL

### TRAIN MODEL

### OUTPUT

---

**TRAINING SET**

**PREDICTION SET**

<table>
<thead>
<tr>
<th>geometry</th>
<th>type</th>
<th>year</th>
<th>height</th>
<th>floors</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSMRI1O...</td>
<td>1</td>
<td>1970</td>
<td>12</td>
<td>4</td>
</tr>
<tr>
<td>AHC39LS...</td>
<td>4</td>
<td>1935</td>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>KDF87L9...</td>
<td>3</td>
<td>2005</td>
<td>24</td>
<td>8</td>
</tr>
</tbody>
</table>

...
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

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**NEIGHBORHOOD SCALE**

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

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**URBAN SCALE**

- Built coverage ratio
- Average building height
- Building aspect ratio
\[ sp_i = \tan\left(\frac{h_i}{d}\right) \cdot \min\left(\frac{h_i}{h}, 1.1\right) \]
**Input**

**Prepare Data**

**Select Model**

**Train Model**

**Output**

### Urban Scale

**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.
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...
INPUT
PREPARE DATA
SELECT MODEL
TRAIN MODEL
OUTPUT

BROC

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%
INPUT
PREPARE DATA
SELECT MODEL
TRAIN MODEL
OUTPUT

TURIN

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

• 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
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!
Feel free to contact me for any question!

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