Using shape, proximity and functionality to define neighborhoods with morphologically similar buildings

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Urban Patterns session
7 September 2019

UNIL | Université de Lausanne
Institut de géographie et durabilité

ECTQG 2019 Luxembourg

What, how, and why ?

- Trying to cluster morphologically similar buildings in an urban context
- Using features derived from simple building representations
- Clustering using a geo-constrained Self-Organizing Map (geo-SOM)
- Find (in-)homogeneous places in cities, compare internal morphologies of cities, etc.

Approaches

Literally the *study of urban form*, with several approaches (Kropf, 2017)

- Typo-morphological (evolution of building types)
- Configurational (topological relations, influence of spatial configuration)
- Historico-geographical (townplan study, hierarchy of elements)
- Spatial analytical (complex systems, physical and socio-economical dynamics)

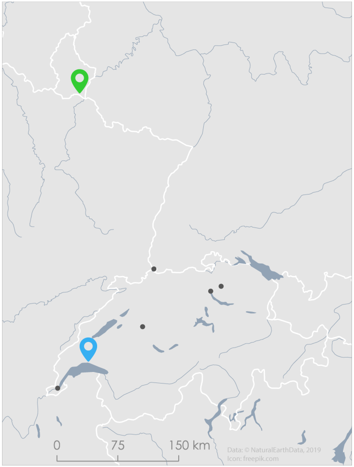
Similar works

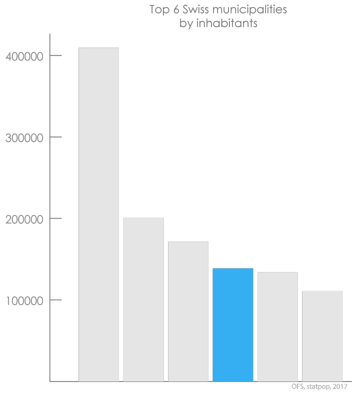
- Schirmer and Axhausen (2015;2019) proposed a set of features at multiple scales on which to apply clustering. They used it to quantitatively describe the urban morphology
- Steiniger *et al.* (2008) morphologically characterized building geometries and classified them for cartographic generalization
- Fan, Zipf, and Fu (2014)

Similar works

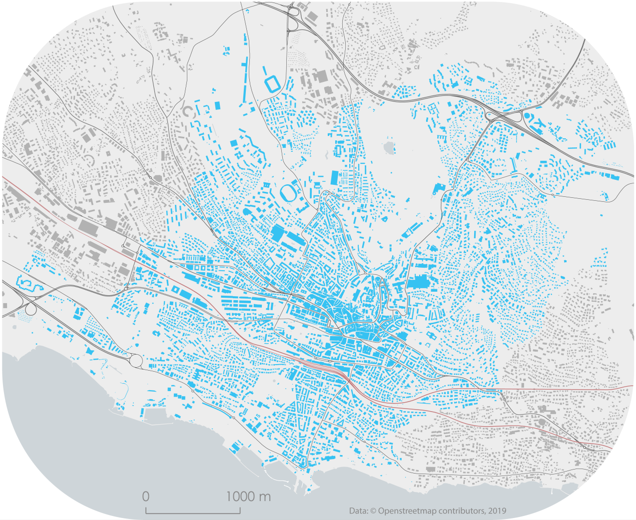
- Schirmer and Axhausen (2015;2019)
- Steiniger *et al.* (2008)
- Fan, Zipf, and Fu (2014) used a turning function to find similar footprints of buildings. They tried to classify the morphologies into (functional) types. They also developed a rule-based approach to estimate the type of a building according to its characteristics

Lausanne, Switzerland



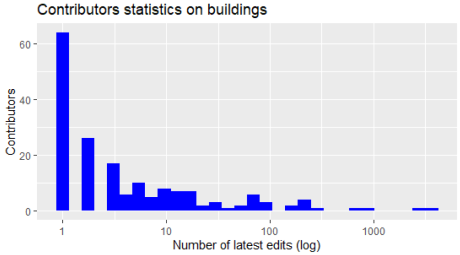


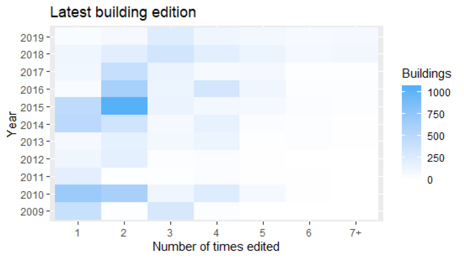
Lausanne Municipality



OpenStreetMap data - Gathering footprints

- Open data generated by multiple contributors
- Available on a global scale but unevenly distributed
- Quality depending on several factors (available imagery, familiarity of the cartographer, etc.)





Selected features overview

OSM buildings in Lausanne	9850	
height specified	3	0.03%
number of levels specified	549	5.57%
type specified	2089	21.21%
levels and type specified	451	4.58%

OpenStreetMap data - Gathering footprints

- Open data generated by multiple contributors
- Available on a global scale but unevenly distributed
- Quality depending on several factors (available imagery, familiarity of the cartographer, etc.)
- Limits: High geometrical variability, features of interest not sufficiently filled

Swisstopo data - Computing height

- Digital Elevation Model, 2016, 2m resolution, 0.5m accuracy
- Digital Surface Model, 2016, 2m resolution, 0.5m accuracy
- Compute the difference and assign mean value of cells intersecting each building
- Gives a sufficient approximation of the building height

Buildings and housing registry - Retrieving categories

- Central registry maintained by the Federal Statistical Office
- Data input by the municipalities
- General categories (6) and specific classes (26) adapted from EUROSTAT
- Quality assurance ?

Indicators derived - Feature creation

- Merged adjacent buildings and remove odd valued ones (e.g. negative height)
- Features based on the footprint geometry and the height
- Inspired by Schirmer and Axhausen (2015) with several additions (oriented envelope, compactness)

- Quite correlated and redundant
- How to select the most suitable ones

Model-based clustering

- Using the method implemented by Ceuleux *et al.* (2014)
- Simultaneously selects the number of clusters and a set of *relevant* features
- Gives a clustering based on features

(Geo-)SOM

The Self-Organizing Map was proposed by Kohonen (2001)

- From a high-dimensional dataset to a simpler (2D) output/representation
- Initialisation of neurons with a weights vector corresponding to the dimensions of the dataset
- Competitive and adaptive learning

Geo-SOM

A SOM with a geo constraint Bação *et al.* (2005)

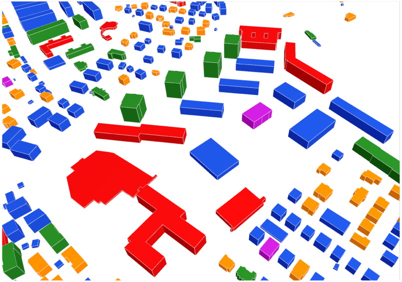
- Take the data point
- Find the (spatially) closest neuron
- Look into it and its neighbours to find the most similar
- Adjust the BMU and its neighbours and repeat with the next data point

- Different adaptable parameters: size of the map, neighbourhood type, number of searchable neighbours

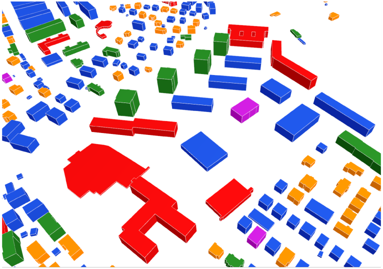
Input

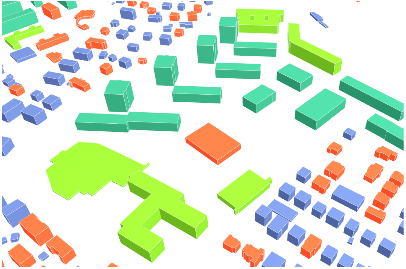
Example of result with 15 hand-picked features, reduced to:

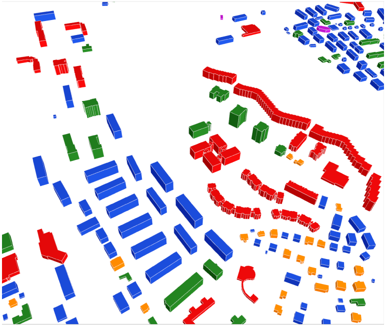
- Perimeter
- Area
- Ratio volume to facade
- Length of longest edge
- Height
- Ratio area to convex hull area
- Ratio perimeter to convex hull perimeter
- Ratio width/length of oriented envelope
- Number of skeleton deadends


Feature based


© google, 2019


Feature based


Geosom based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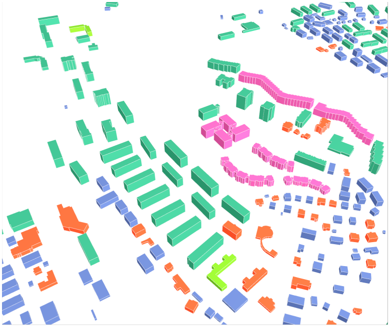
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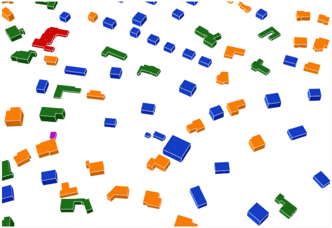

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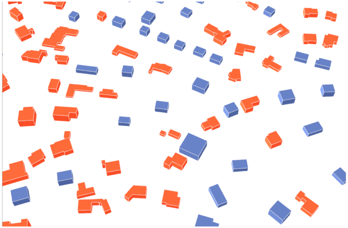
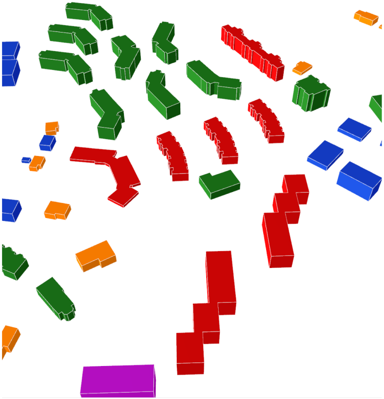


Geosom based

Still progress to be made



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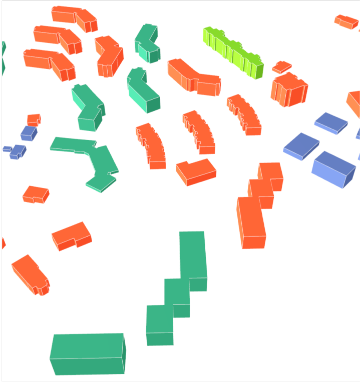

Geosom based

Main difficulties and open questions

- Clustering and lack of results comparisons
- Can the features allow the discovery of relevant results ?
- *What is a building ?* (garages, sheds, stadiums, etc.)

Future works

- Experimenting with the geo-SOM parameters
- Switch from the centroids to a proximity-based relation
- Incorporate the functions of buildings in a meaningful way
- Try an approach based on computer vision

Thanks for your attention

Slides, routines (and more) will be available on *GitHub*
`https://github.com/Raphbub/`

For any further questions, remarks or suggestions
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Geo-SOM

A Self-Organizing Map with a geographical constraint

Data normalized into range $[0, 1]$

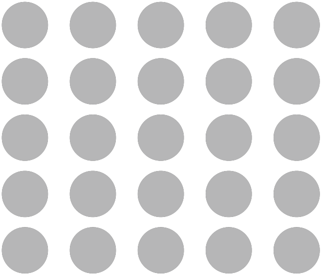
Data as n-dimensional vectors d

$$d = [x_{coord}, y_{coord}, \xi_1, ..., \xi_n]^T$$

Initialisation of a map with

$l \times m$ neurons n

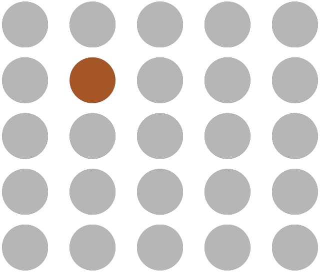
$$n = [x_{coord}, y_{coord}, \mu_1, ..., \mu_n]^T$$



Geo-SOM

For each d, find the most spatially similar neuron

$$Geo_{BM} = \min_i ||d_{xy} - n_{xy}||$$



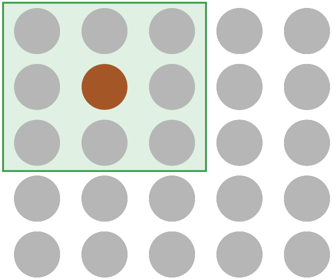
Geo-SOM

For each d, find the most spatially similar neuron

$$Geo_{BM} = \min_i ||d_{xy} - n_{xy}||$$

Then, find the most similar neuron in its neighbours

$$BMU = \min_j ||d - n||$$
$$with\ n \in Geo_{BM}\ neighbours$$



Geo-SOM

The BMU and its neighbours are updated

$$n_i(t+1) = n_i(t) + h_{ci}(t)[d(t) - n_i(t)]$$

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K-Means is applied on the final SOM (Flexer, 2001)

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Data vectors are assigned groups using the previous steps