Features of districts of Warsaw visible from space

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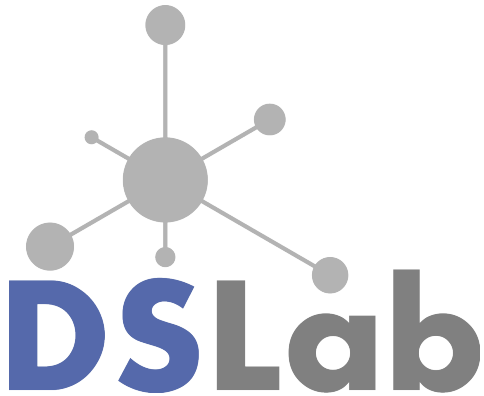
UNIVERSITY OF WARSAW
Faculty of Economic Sciences

About Data Science Lab



Data Science Lab is an organization created in 2019 at the Faculty of Economics of the University of Warsaw.

We are a group consisting of academic workers, business professionals and students who were gathered together by our passion for uncovering the unknown and discovering practical applications to new tools and methods in data analysis, Machine Learning and Artificial Intelligence.

Aim of the project

- use features visible from space to proxy the level of well-being
- apply machine learning tools using indicators of well-being for administrative areas as outcomes
- apply models for non-administrative areas to predict economic well-being or economic potential
- work in progress

Measuring inequalities from space

- night-time lights intensity used but imperfect (e.g. scale limitations)
- alternative: high-resolution daytime satellite pictures

Economic and business applications

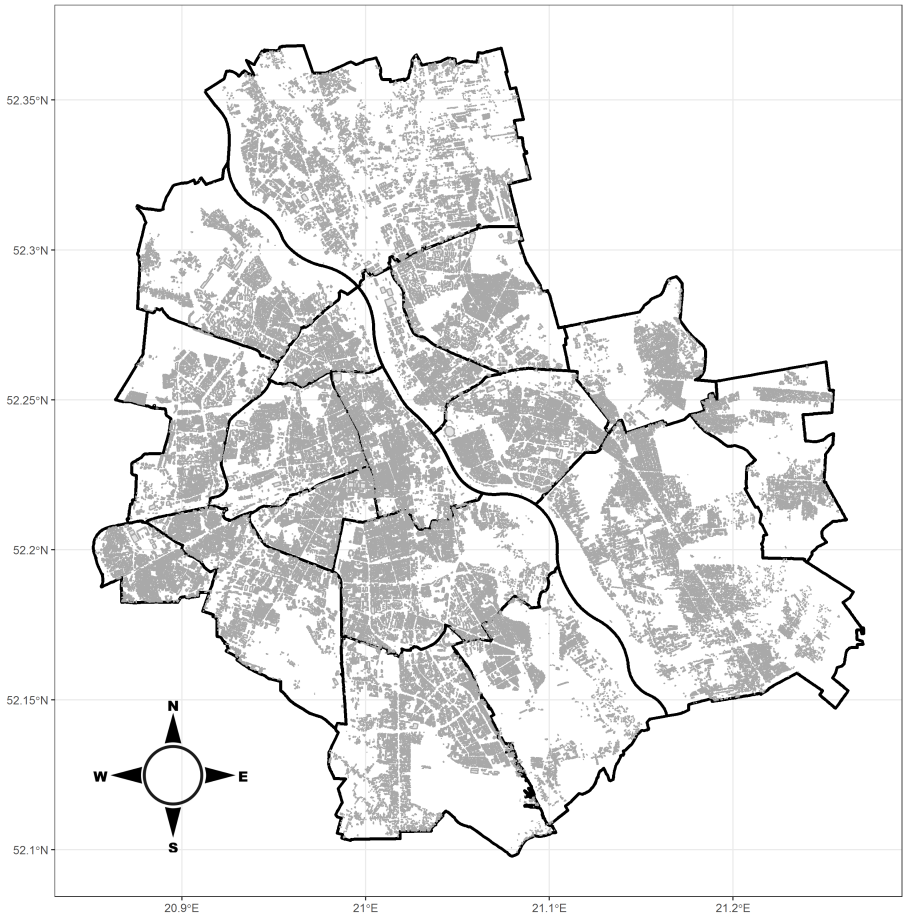
- can be easily **aggregated for any territorial units**
- **independent** of politicians and response rates in surveys
- increasingly used as a **proxy of economic activities** at the regional and local level (e.g. Nature, 2017)
- it has informational value for **countries with poor quality of national income accounts**
- proxies for **economic well-being** or **market potential** can be calculated for **non-administrative areas** (e.g. **specific business regions**)

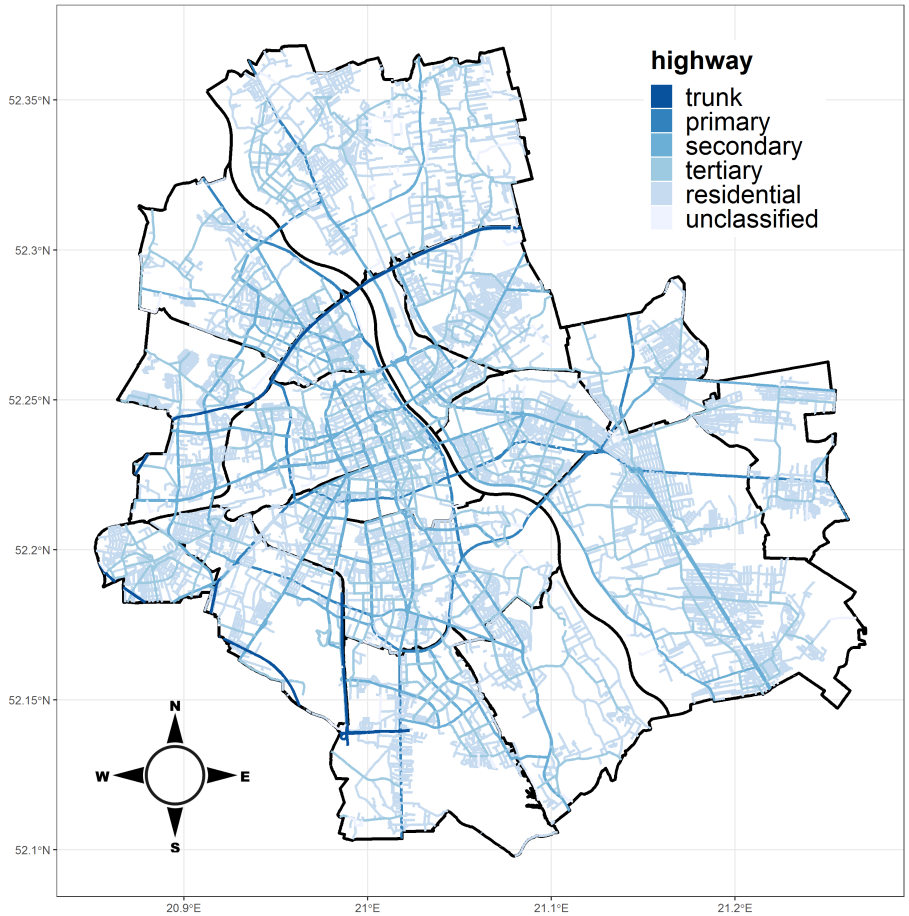
Data sources

- Open Street Map – localisation of buildings, streets, rivers and lakes, green areas, public transport, bike rental, fuel stations, supermarkets and malls
- Google Maps: 6000+ high-resolution daytime images of Warsaw from space
- socio-economic indicators for Warsaw districts:
  - budget 2019 – real spendings
  - Panorama of Warsaw districts (2017) – total income, income share in PIT/CIT, population (total, men, women), vehicles (total, passenger)
  - report "Health condition of Warsaw residents" (2016) – life expectancy

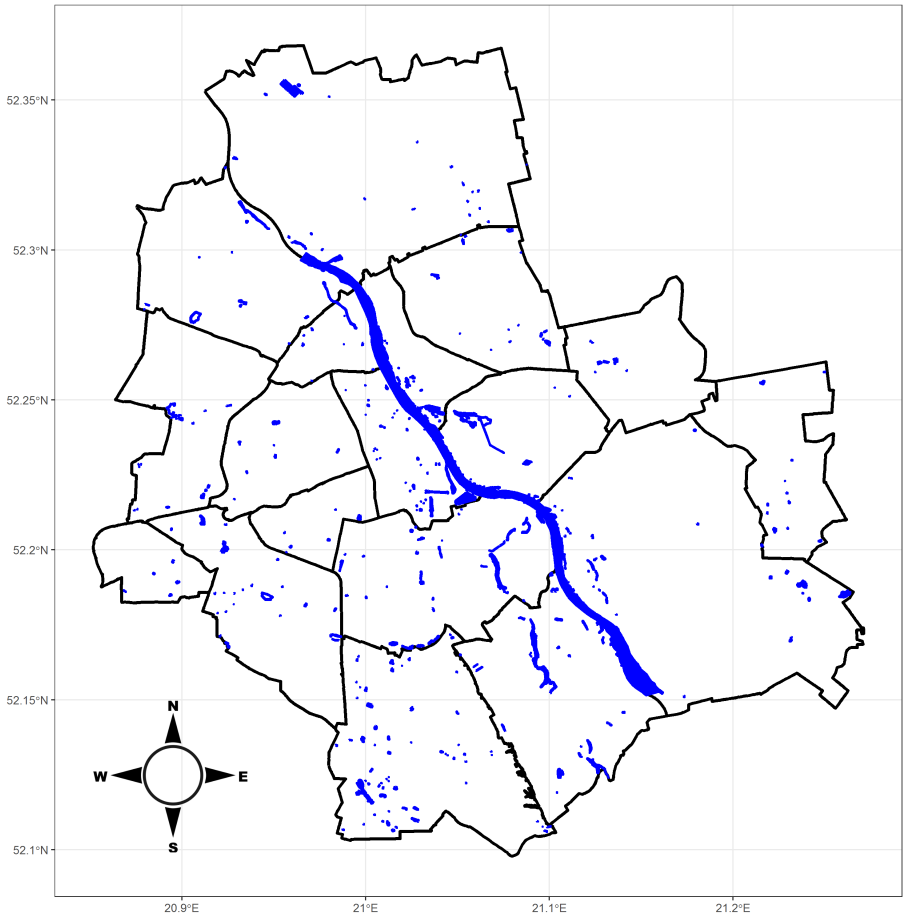
Identifying objects on satellite images

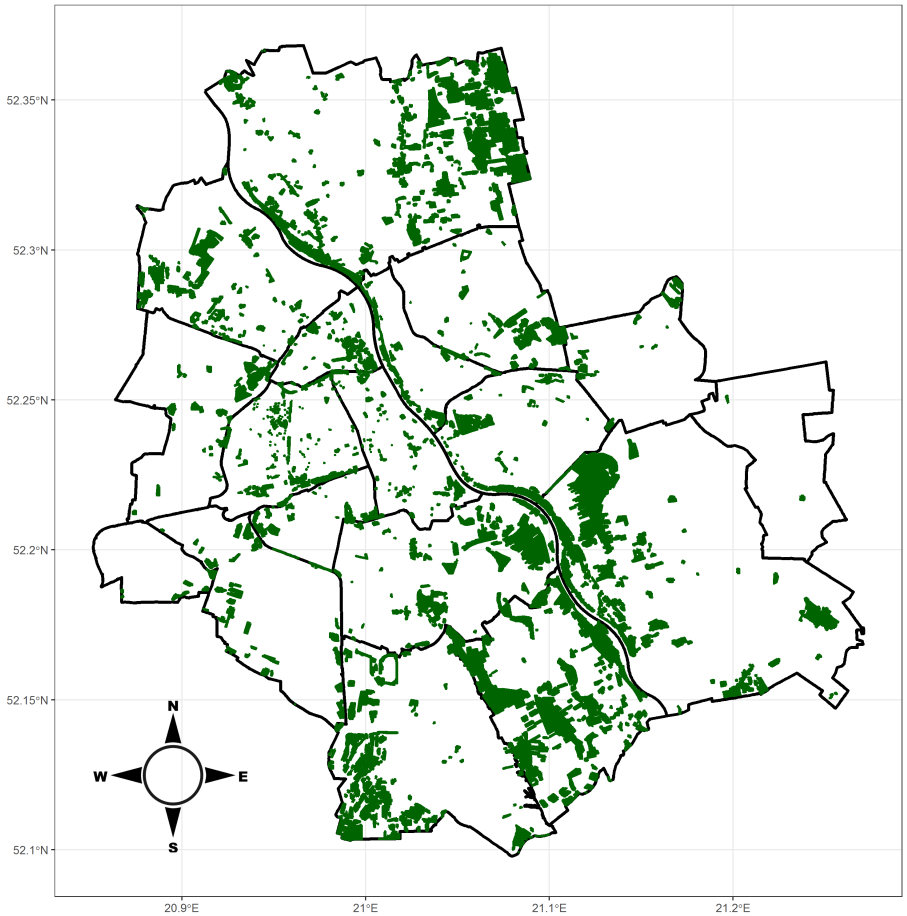
OSM buildings and streets by type



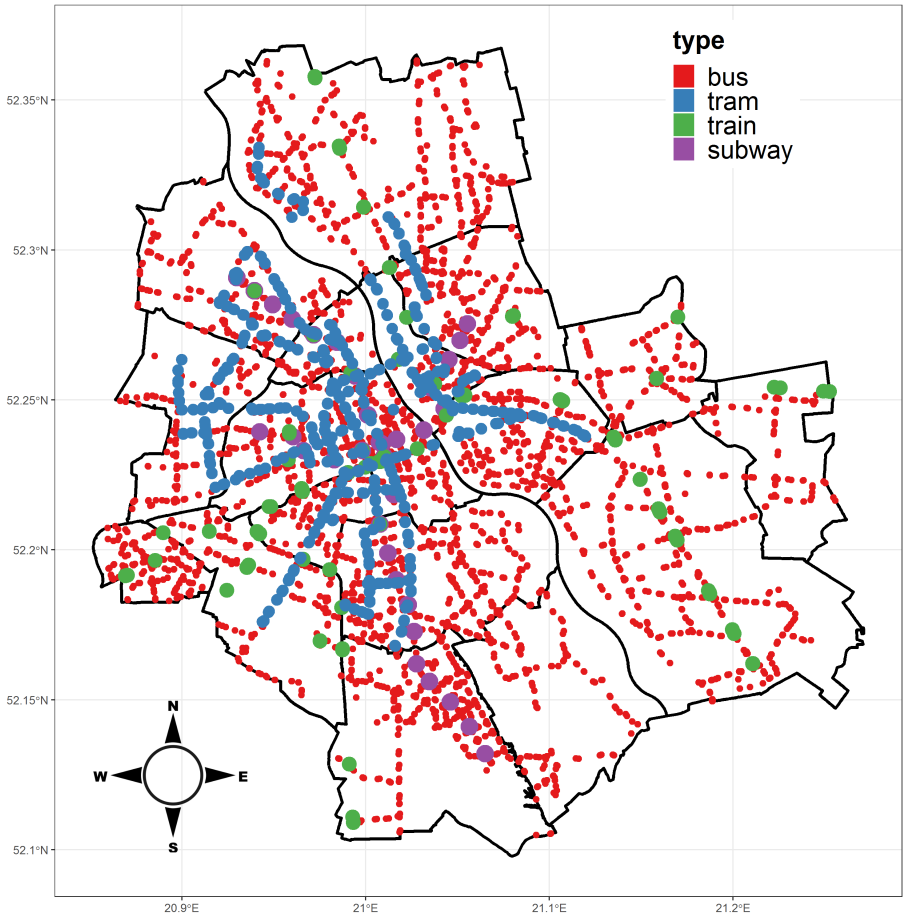


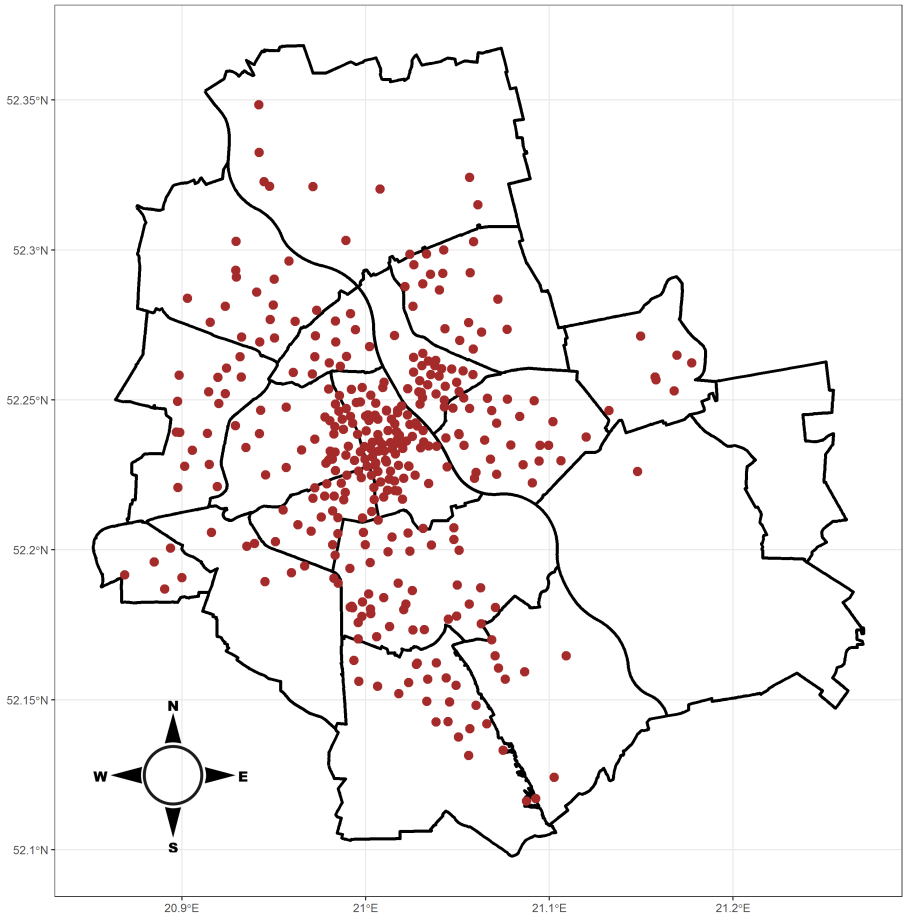
OSM water and green areas



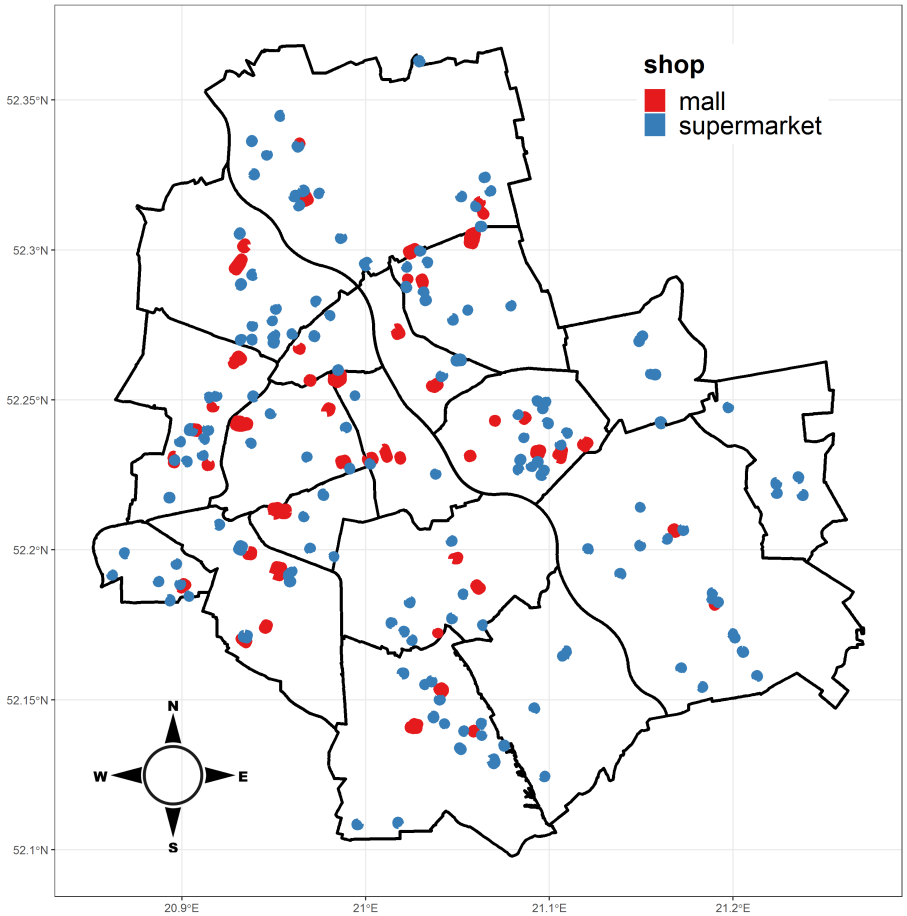


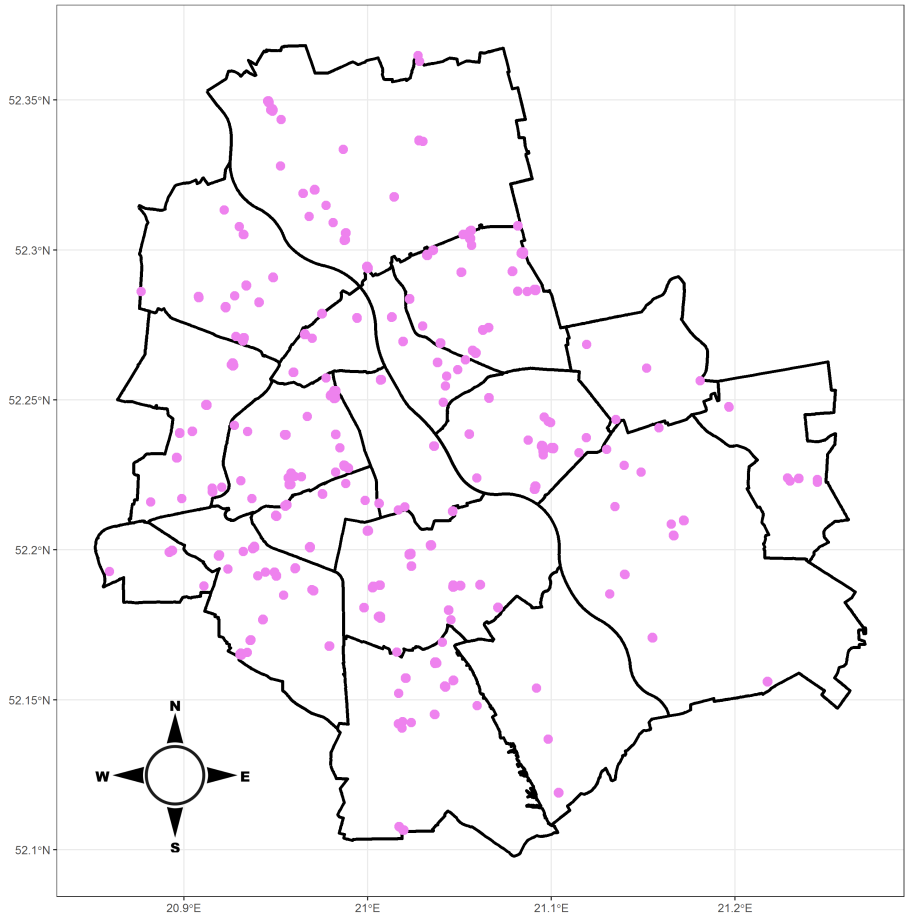
OSM public transport (stops by type) and bike rental (Veturilo stations)



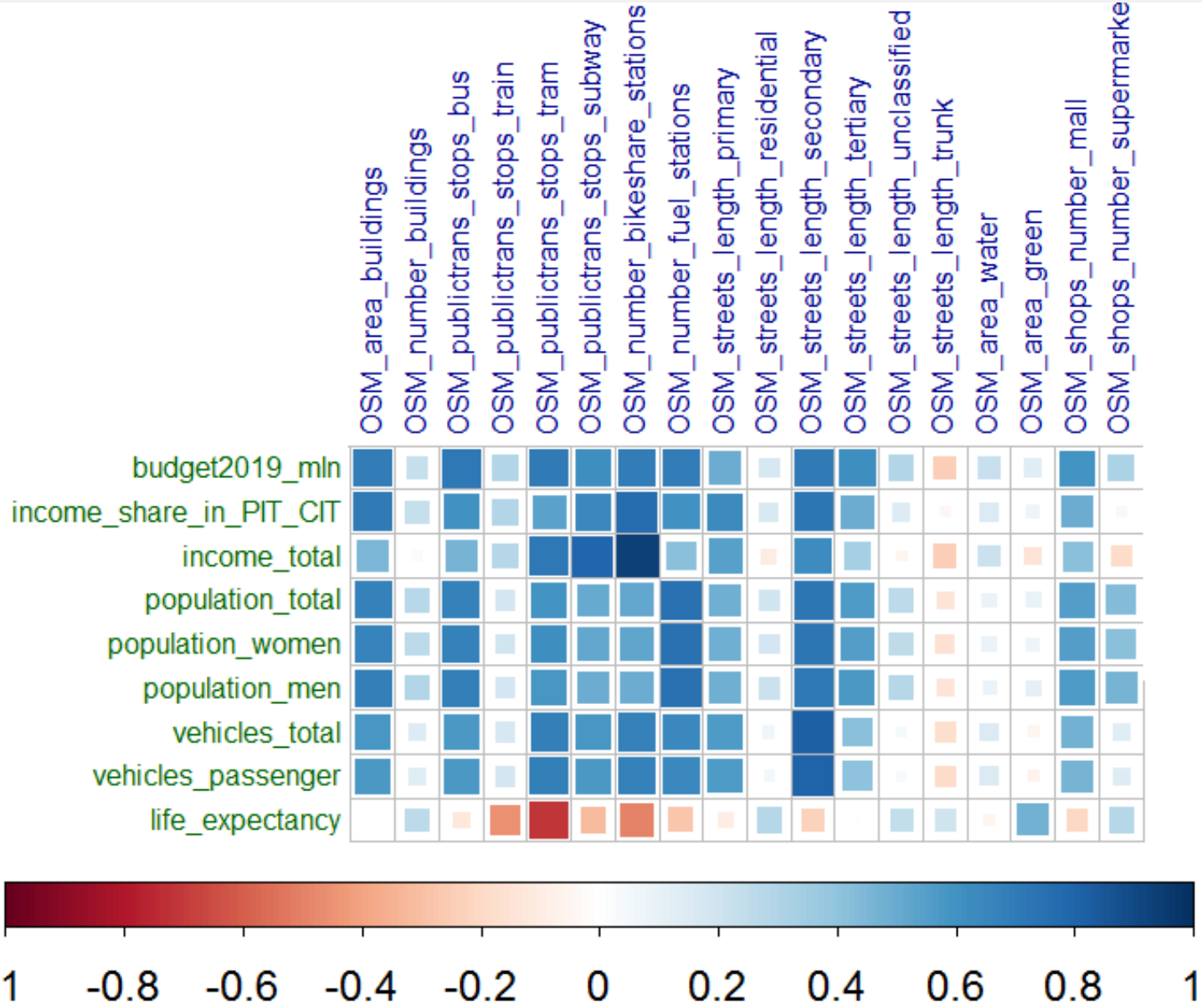


OSM supermarkets and fuel stations





Correlation between OSM extracted features and indicators



OSM feature importance based on LASSO

	variable	budget2019_mln	income_share_in_PIT_CIT	income_total	population_total	population_women	population_men	vehicles_total	vehicles_passenger	life_expectancy
LASSO	OSM_number_bikeshare_stations		1	2	6	4		2	2	5
	OSM_number_fuel_stations			4	5	1	1	4	4	8
	OSM_publictrans_stops_bus				7	3	2			7
	OSM_publictrans_stops_tram				3	2				4
	OSM_shops_number_mall			6	2			1	1	1
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	OSM_area_buildings		3	13	14					14
	OSM_area_green				13			8	8	16
	MAE	197.25	19270.77	52750.28	47211.16	23124.53	19630.11	33544.59	29918.29	4.62
	MAPE	0.649	0.600	0.846	0.539	0.632	0.636	0.550	0.588	0.060

OSM feature importance based on random forest

	variable	budget2019_mln	income_share_in_PIT_CIT	income_total	population_total	population_women	population_men	vehicles_total	vehicles_passenger	life_expectancy
RF	OSM_number_bikeshare_stations	1	3	2	1	1	1	2	1	1
	OSM_number_fuel_stations	5	10	9	5	4	6	5	5	11
	OSM_publictrans_stops_bus	4	9	8	4	5	4	6	6	13
	OSM_publictrans_stops_tram	6	2	3	10	10	12	4	4	4
	OSM_shops_number_mall	3	4	6	3	3	3	8	7	17
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	OSM_area_buildings	7	7	11	7	7	7	9	9	14
	OSM_area_green	12	16	17	15	15	15	15	16	10
	MAE	128.39	18053.00	81590.29	34313.99	18808.38	15505.85	35024.39	29581.98	1.70
	MAPE	0.390	0.605	1.352	0.518	0.532	0.501	0.678	0.711	0.022

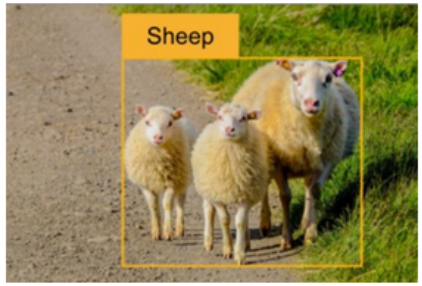
Feature extraction from satellite images

- Features extracted from OSM were used to label objects on satellite images.
- Buildings were recognized in pictures using deep neural networks.
- Transfer learning was performed based on models pre-trained on Imagenet.
- Dataset was split proportionally on district level.
- Better estimations of green areas were calculated.

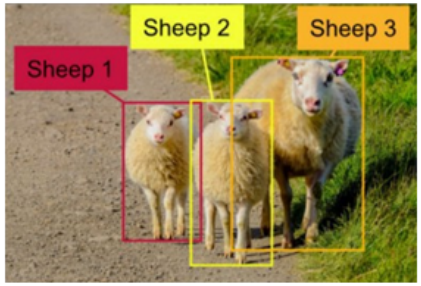
Types of problems in computer vision

Image classification

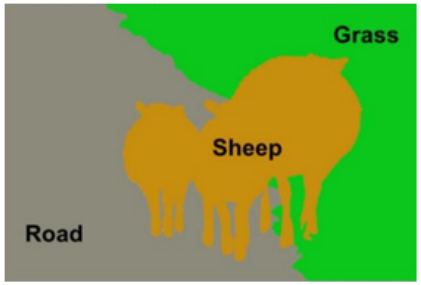
Classification with Localization



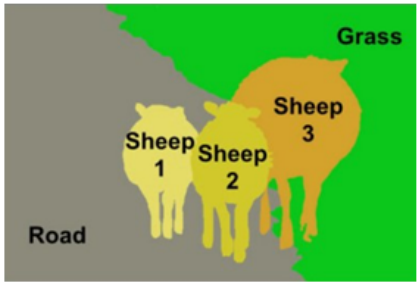
Object detection



Semantic segmentation



Instance segmentation



Transfer learning

- Problem: Training a neural network requires time and powerful computational resources.
- Possible solution: Transfer learning
  - The model is not trained from scratch, but uses a model pre-trained on a large benchmark dataset to solve a similar problem.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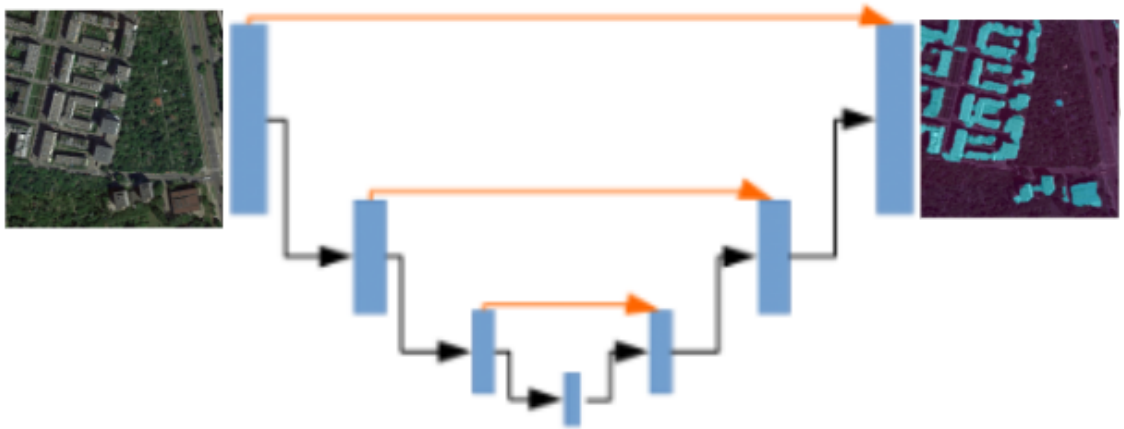
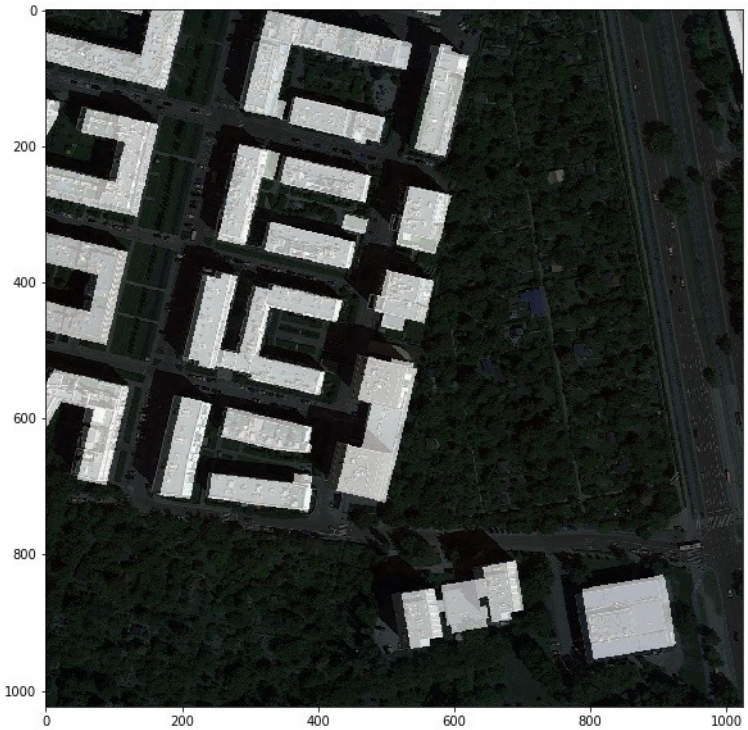
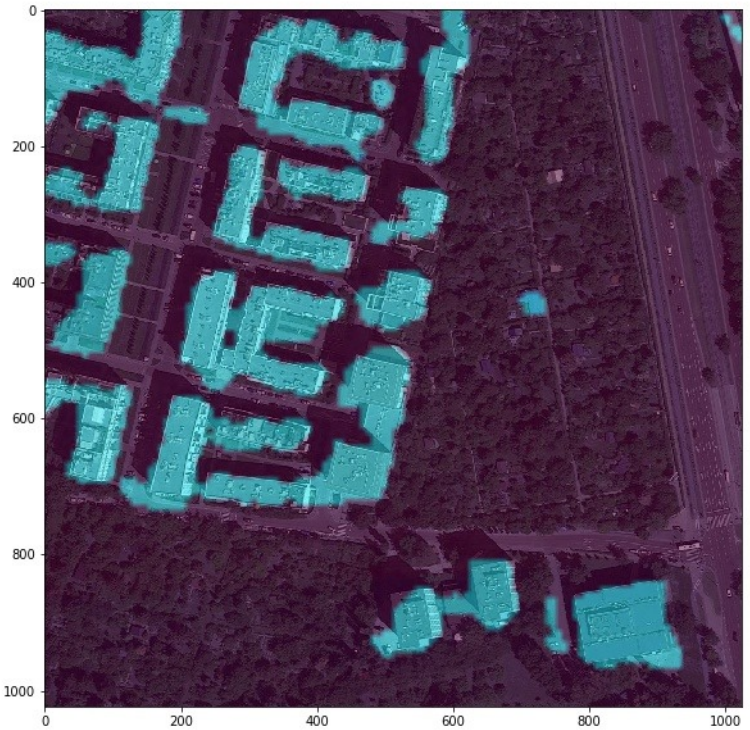
Unet and ResNet101

- ResNet is one of the known, state-of-the-art architectures with an open source pretrained model.
  - It is used to classify images, resulting in a single value.
- By removing the top dense layers of the network, model outputs a vector of values.
- In a U-Net, an image is converted into a vector and then the same mapping is used to convert it again to an image.
  - It is used for classification per pixel, not per image.



True and predicted images





Preliminary results

District	Corr	District	Corr
Żoliborz	0.85	Targówek	0.69
Śródmieście	0.85	Ochota	0.68
Rembertów	0.83	Mokotów	0.68
Praga-Południe	0.75	Wilanów	0.64
Bielany	0.75	Ursynów	0.64
Białołęka	0.74	Wawer	0.59
Wesoła	0.74	Praga-Północ	0.59
Włochy	0.74	Wola	0.55
Bemowo	0.73	Ursus	0.19

- Predicted area of buildings was calculated.
- Correlations between true and predicted area percentage values look promising.
- It could look better but we encountered some obstacles...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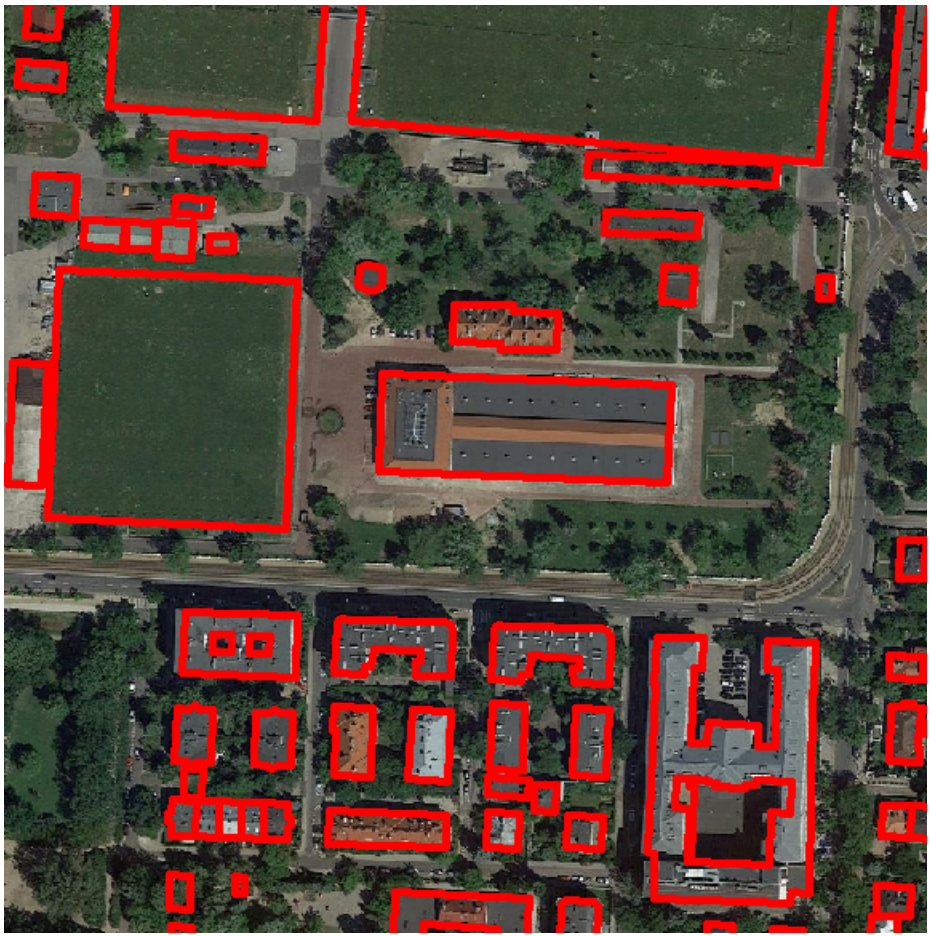
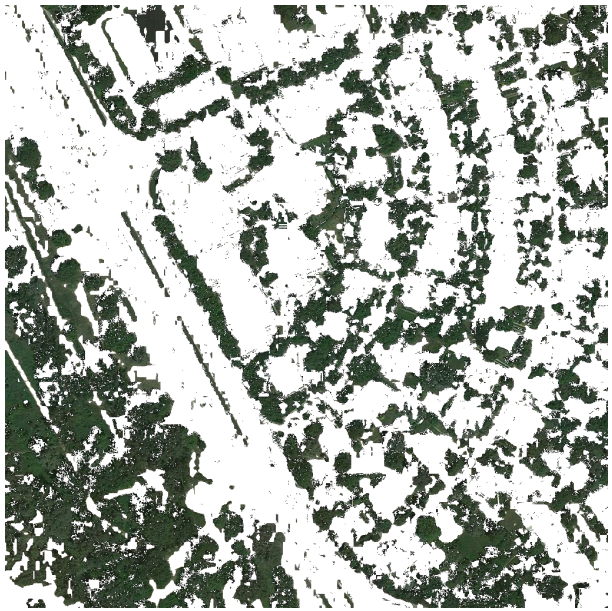
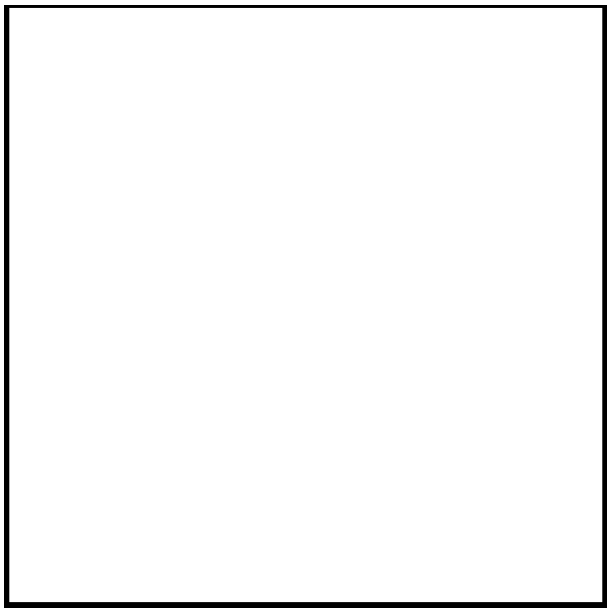
Examples of problematic images



Improving green area labels

- Green areas in OSM are poorly labelled.
- It can be done better by extracting only pixels in chosen color channel ranges.





OSM feature importance based on LASSO + predicted variables

	variable	budget2019_mln	income_share_in_PIT_CIT	income_total	population_total	population_women	population_men	vehicles_total	vehicles_passenger	life_expectancy
LASSO	OSM_number_bikeshare_stations		1	2	6	4		2	2	5
	OSM_number_fuel_stations			4	5	1	1	4	4	8
	OSM_publictrans_stops_bus				7	3	2			7
	OSM_publictrans_stops_tram				3	2				4
	OSM_shops_number_mall			6	2			1	1	1
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	OSM_area_buildings		3	13	14					14
	OSM_area_green				13			8	8	16
	MAE	197.25	19270.77	52750.28	47211.16	23124.53	19630.11	33544.59	29918.29	4.62
	MAPE	0.649	0.600	0.846	0.539	0.632	0.636	0.550	0.588	0.060
LASSO (w/ pred variables)	OSM_number_bikeshare_stations		2	2	4	4		1	2	6
	OSM_number_fuel_stations		6	4	3	1	1	4	4	8
	OSM_publictrans_stops_bus				6	3	2			7
	OSM_publictrans_stops_tram		7		5	2		5	5	4
	OSM_shops_number_mall		1					2	1	5
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	OSM_area_buildings_pred		15							15
	OSM_area_green_pred							9	9	16
	MAE	197.25	32043.48	56837.23	40367.19	23124.53	19553.72	34638.79	30788.64	4.28
	MAPE	0.649	1.026	0.846	0.526	0.632	0.633	0.570	0.598	0.056

OSM feature importance based on random forest + predicted variables

	variable	budget2019_mln	income_share_in_PIT_CIT	income_total	population_total	population_women	population_men	vehicles_total	vehicles_passenger	life_expectancy
LASSO	OSM_number_bikeshare_stations	1	3	2	1	1	1	2	1	1
	OSM_number_fuel_stations	5	10	9	5	4	6	5	5	11
	OSM_publictrans_stops_bus	4	9	8	4	5	4	6	6	13
	OSM_publictrans_stops_tram	6	2	3	10	10	12	4	4	4
	OSM_shops_number_mall	3	4	6	3	3	3	8	7	17
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
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	MAPE	0.390	0.605	1.352	0.518	0.532	0.501	0.678	0.711	0.022
LASSO (w/ pred variables)	OSM_number_bikeshare_stations	1	2	2	1	1	1	2	2	1
	OSM_number_fuel_stations	5	7	10	3	3	4	4	3	12
	OSM_publictrans_stops_bus	4	9	7	5	5	5	7	7	13
	OSM_publictrans_stops_tram	7	3	3	11	9	11	5	4	5
	OSM_shops_number_mall	3	5	9	4	4	3	8	8	17
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	OSM_area_buildings_pred	13	16	16	14	14	14	12	14	16
	OSM_area_green_pred	15	14	6	16	16	16	16	16	2
	MAE	129.64	18594.46	77569.34	35042.93	19080.28	15920.14	34132.85	28925.08	1.68
	MAPE	0.400	0.651	1.267	0.524	0.537	0.510	0.663	0.694	0.022

Conclusions

- object detection on satellite images requires large computing power and good training data
- well-being prediction requires many variables, not only buildings and green areas
- districts are too big administrative areas but they are the lowest level of financial data publicly available

Further steps

- obtain well-being data on lower level than district, e.g. postal code
- change prediction to classification instead of regression
- add new variables to model, e.g. building height, roof type, building type (offices vs houses)
- obtain data over time to observe changes
- broaden analysis to other areas since metropolies are heterogenous
- use model on areas that have even worse labelled data

Thank you

THANK YOU FOR YOUR ATTENTION!


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