UrbanMindscape: Bridging the Subjective and Objective Perception in Proximate Sensing

Keywords: Urban Perception; Semantic Segmentation; Street View Images; Convolutional Neural Network (CNN); Deep Learning

BACKGROUND

Street View Images(SVI) have been a valuable resource in different contexts.



Urban Analysis of the Built Environment

Infrastructure Management

Environmental Monitoring

Real Estate and Property Management

Public Safety and Security

Social and Economic Research

BACKGROUND

Street View Images(SVI) have been a valuable resource in different contexts.



Urban Analysis of the Built Environment

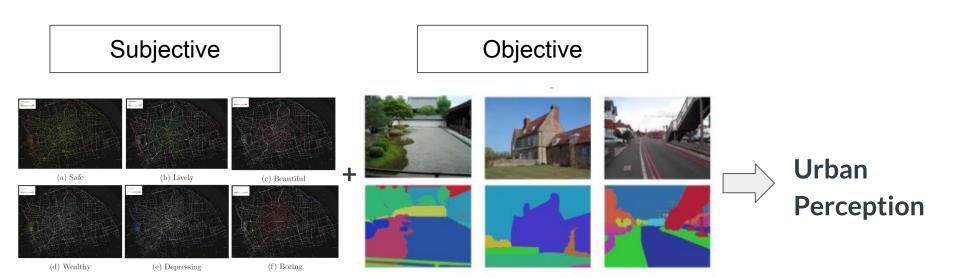
Create visual representations of human perceptions and the physical characteristics of urban environments by leveraging deep learning techniques.

Objective

Subjective

A comprehensive understanding of urban spaces

Background



Human Perception Score

Proximate Sensing

Background

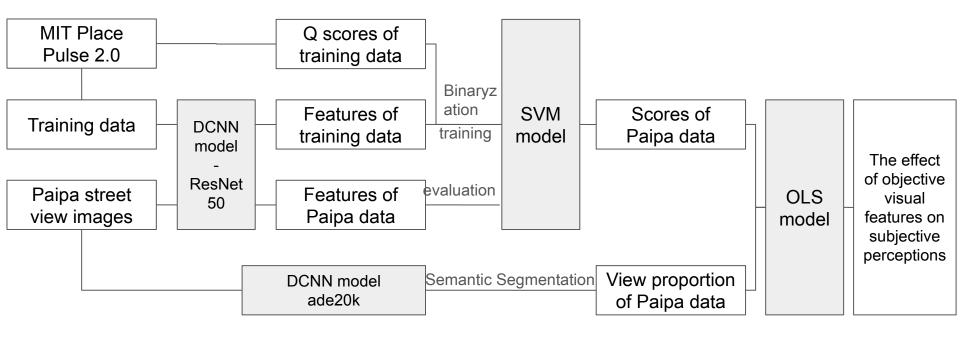
MIT Place Pulse 2.0

Continent	#Cities	#Images
Asia	7	11,342
Africa	3	5,069
Australia	2	6,082
Europe	22	38,636
North America	15	33,691
South America	7	16,168
Total	56	110,988

The user interface of the MIT Place Pulse data collection platform. Participants are asked to choose one of the two images in response to one of the six questions. Millions of human perception responses for the images have been collected.



Methods



Experiment

Study Area:

Train: MIT Place Pulse 2.0 dataset

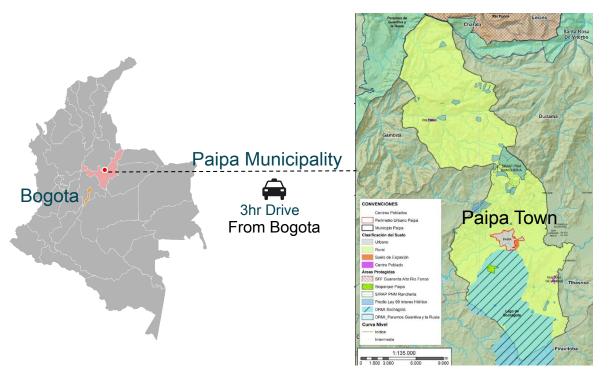
Test: Paipa Town, Colombia

Dataset:

MIT Place Pulse 2.0 street view images across the world

MIT Place Pulse 2.0 Q scores of SVI in six human perceptions

Paipa street view images(10m distance)



Experiment

To avoid introducing noise and error as much as possible, I followed the paper reference here and selected representative positive/negative samples from the whole dataset to use for the training task.

$$y_i^{\nu} = \begin{cases} -1 & \text{if} \quad Q_i^{\nu} < \mu_{\nu} - \delta \sigma_{\nu} \\ 1 & \text{if} \quad Q_i^{\nu} > \mu_{\nu} + \delta \sigma_{\nu} \end{cases}$$

Zhang, F., Zhou, B., Liu, L., Liu, Y., Fung, H.H., Lin, H., Ratti, C., 2018. Measuring human perceptions of a large-scale urban region using machine learning. Landscape and Urban Planning 180, 148–160. https://doi.org/10.1016/j.landurbplan.2018.08.020

•	Safe	6.3	1
•	Beautiful	5.3	1
•	Wealthy	5.5	1
•	Lively	6.0	1
•	Boring	2.3	-1
	Depressir	na 16	-1

Binaryzation

Q_label	features	image_id	study_question	trueskill.stds1	Q	location_id	
-1.0	[0.22940833866596222, 1.0244624614715576, 0.01	513e6df2fdc9f0358700c383	safer	3.056702	20.592330	513e6df2fdc9f0358700c383	0
1.0	[0.12468238919973373, 0.5190224647521973, 0.04	5140cc3efdc9f04926002d59	safer	2.886764	28.707450	5140cc3efdc9f04926002d59	4
-1.0	[0.06582643836736679, 0.41787010431289673, 0.0	50f5ec0dfdc9f065f0008640	safer	4.895043	20.298309	50f5ec0dfdc9f065f0008640	5
-1.0	[0.34781795740127563, 0.6622889041900635, 0.12	50f60121beb2fed6f80001b8	safer	4.151866	18.482701	50f60121beb2fed6f80001b8	6
1.0	[0.12155959755182266, 0.771874725818634, 0.020	5142183ffdc9f04926008100	safer	5.197565	27.814428	5142183ffdc9f04926008100	8
			***		***		
1.0	[0.4073934257030487, 0.5427781343460083, 0.159	50f5e70dfdc9f065f0007031	safer	3.007945	28.091575	50f5e70dfdc9f065f0007031	19993
-1.0	[0.2706283926963806, 0.8877367377281189, 0.329	50f439edfdc9f065f0002d42	safer	2.759283	16.917069	50f439edfdc9f065f0002d42	19995
1.0	[0.21051648259162903, 1.1483752727508545, 0.06	50f42eabfdc9f065f00022d3	safer	2.884191	33.181343	50f42eabfdc9f065f00022d3	19996
-1.0	[0.057956207543611526, 0.8228529095649719, 0.0	5140cc37fdc9f04926002d47	safer	2.217072	20.803571	5140cc37fdc9f04926002d47	19997
-1.0	[0.3766400218009949, 1.0521074533462524, 0.068	513d5787fdc9f0358700319e	safer	2.397467	20.646238	513d5787fdc9f0358700319e	19999

10922 rows × 7 columns

Which place looks safer?

Which place looks safer?

Which place looks livelier?

Which place looks more boring?

Which place looks wealthier?

Which place looks more depressing?

Which place looks more beautiful?









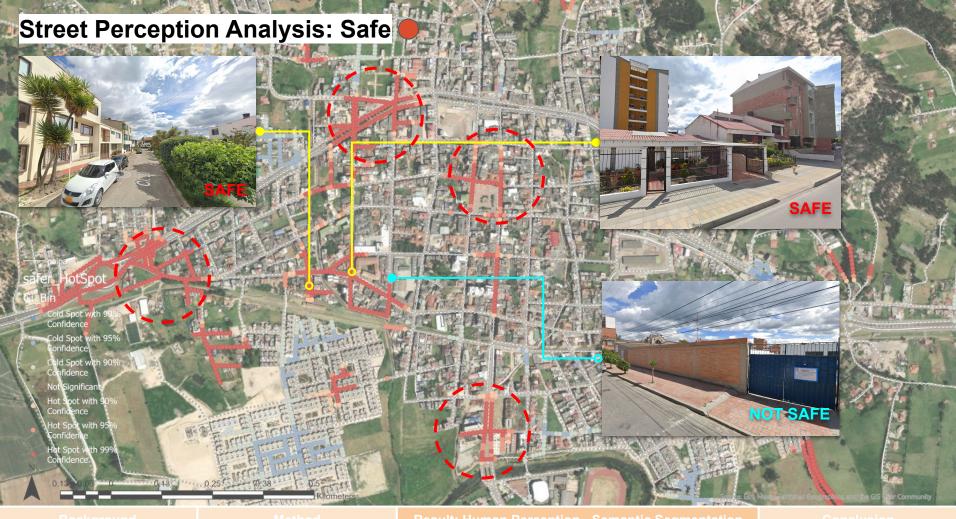
Dubey, A., Naik, N., Parikh, D., Raskar, R., & Hidalgo, C. A. (2016). Deep learning the city:

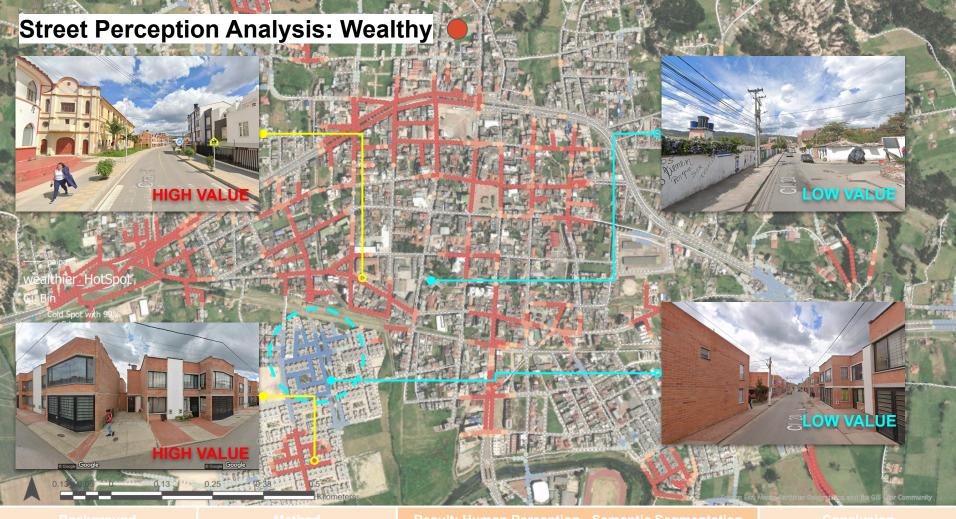


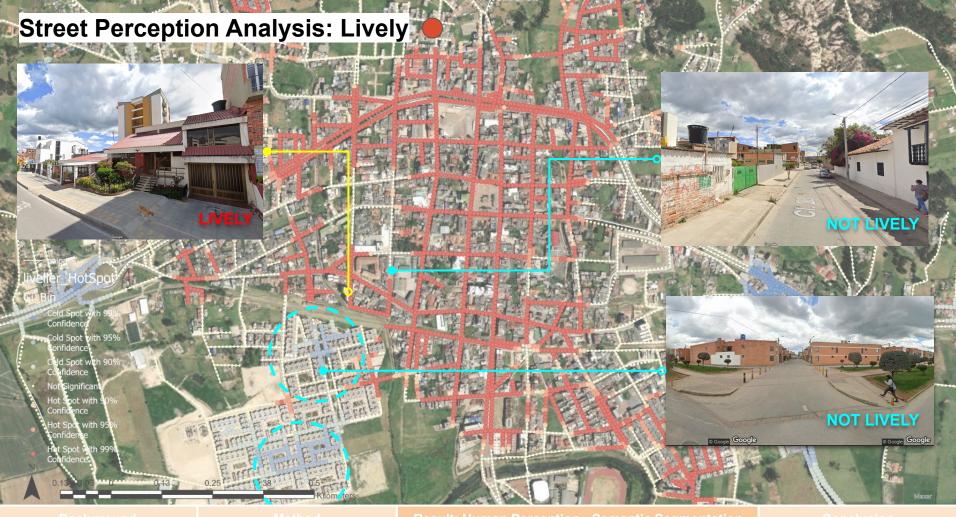
Testing data: 15,000 samples in Paipa

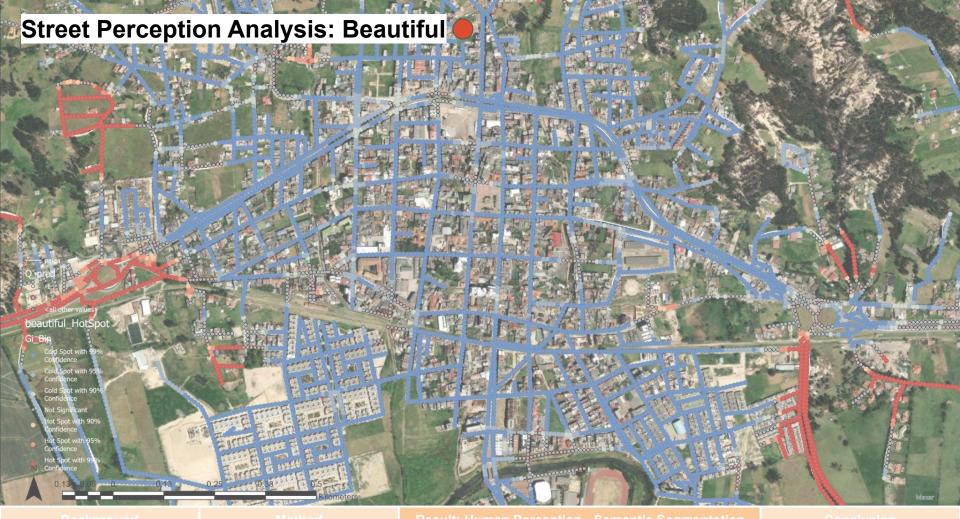
This model answers question:

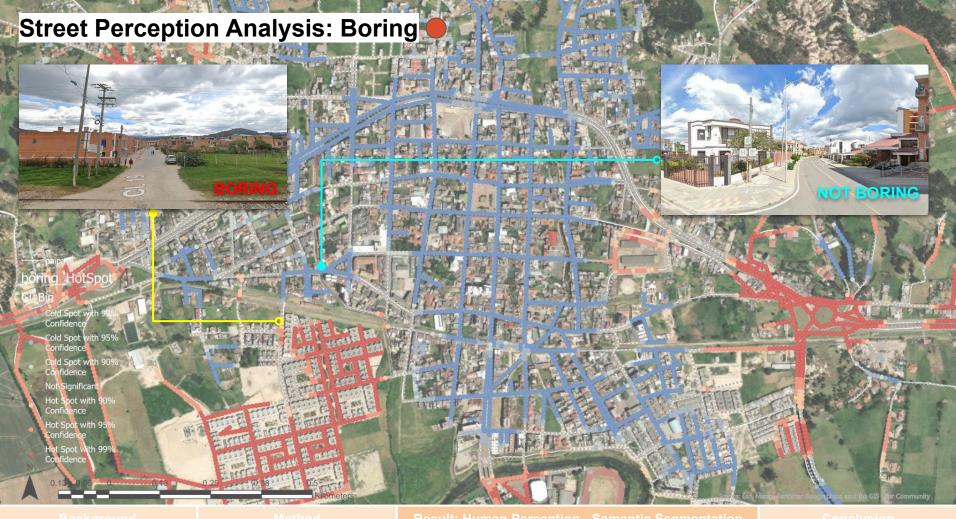
Is this place safe/ lively/ beautiful/ wealthy/ boring/ depressing?

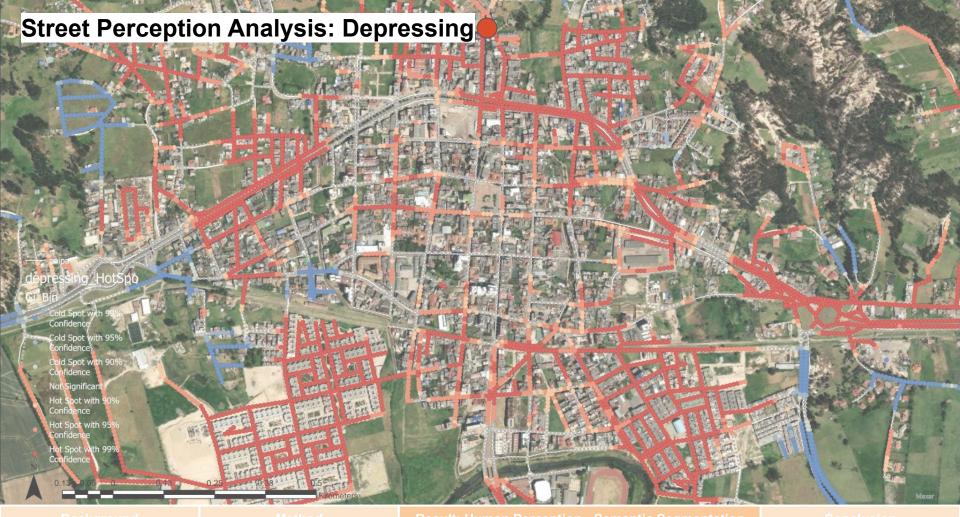




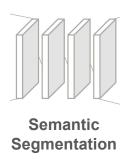


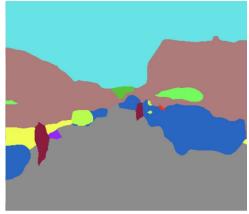












well	0.0013
wan	0.00.0
building	0.1071
sky	0.1700
tree	0.2843
road	0.2251
grass	0.1020
sidewalk	0.0033
plant	0.0001
car	0.0973
sign	0.0035
stairs	0.0002
van	0.0058
	sky tree road grass sidewalk plant car sign stairs

building
car
grass
road
signboard
sky
tree
van
wall

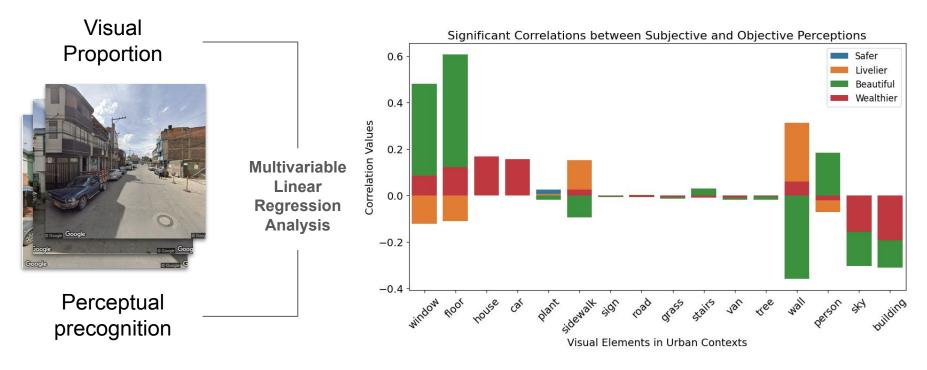
What percentage of the vision is building/car/tree/sky/road...?

Classes related to urban space

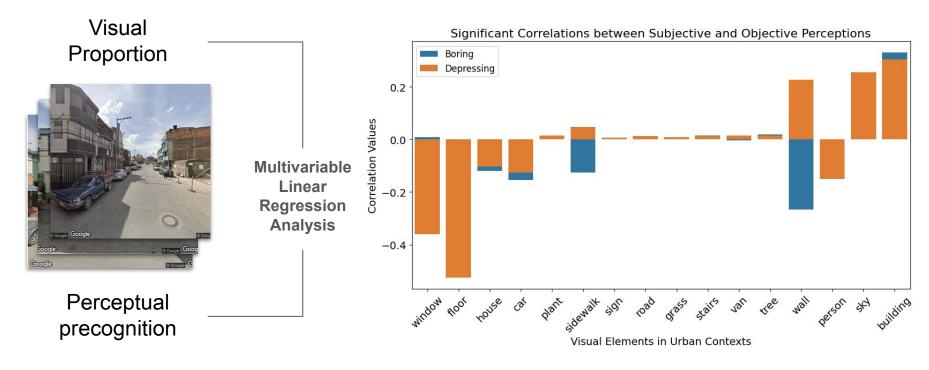
Name	Idx
wall	1
building;edifice	2
sky	3
floor;flooring	4
tree	5
road;route	7
windowpane;window	9
grass	10
sidewalk;pavement	12
person;individual;someone;somebody;mortal;soul	13
plant;flora;plant;life	18
car;auto;automobile;machine;motorcar	21
house	26
signboard;sign	44
stairs;steps	54
van	103







How does the proportion of building/car/tree/sky/road affect the feeling of safe/ lively/ beautiful/ wealthy/ boring/ depressing.

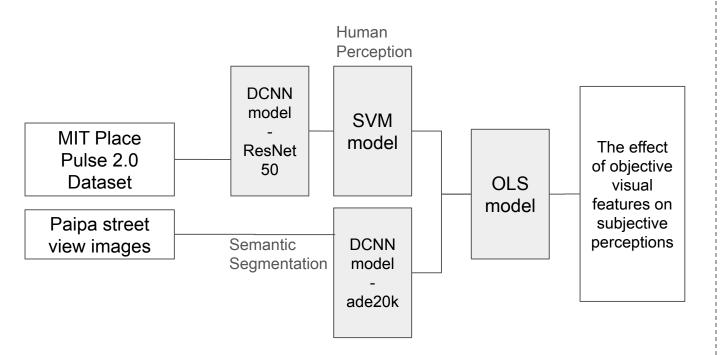


How does the proportion of building/car/tree/sky/road affect the feeling of safe/ lively/ beautiful/ wealthy/ boring/ depressing.

Street Perception Analysis: Design Solution Guidelines

Enhancing green space Unsafe places Unbeautiful places Increasing open public spaces Unlively places **Building Complete Streets Promoting quality housing** Low-value places **Enhancing street walkability** Boring places Depressing places Reducing enclosed spaces

Conclusion



Next Step

Generate a real image of SVI that is a safe/lively/beautiful/wealthy /boring/depressing place

Select the image closest to the center of the custer of safe/lively/beautiful/wealthy /boring/depressing place