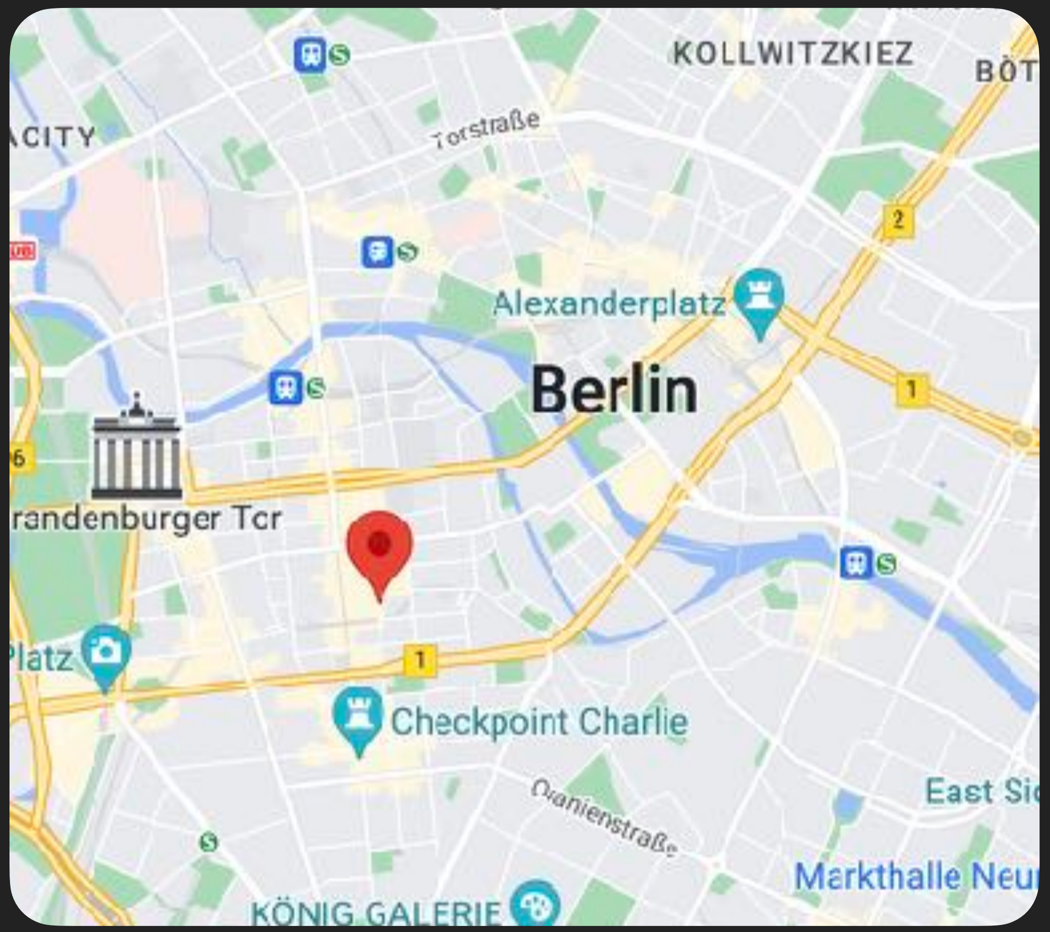
Vers une visualisation située d’une cartographie sensible des villes - Qualification par apprentissage automatique de la perception de l'espace urbain par un piéton en mobilité

Benjamin Beaucamp

10/11/2022 - Webinar “Autour de la 3D”

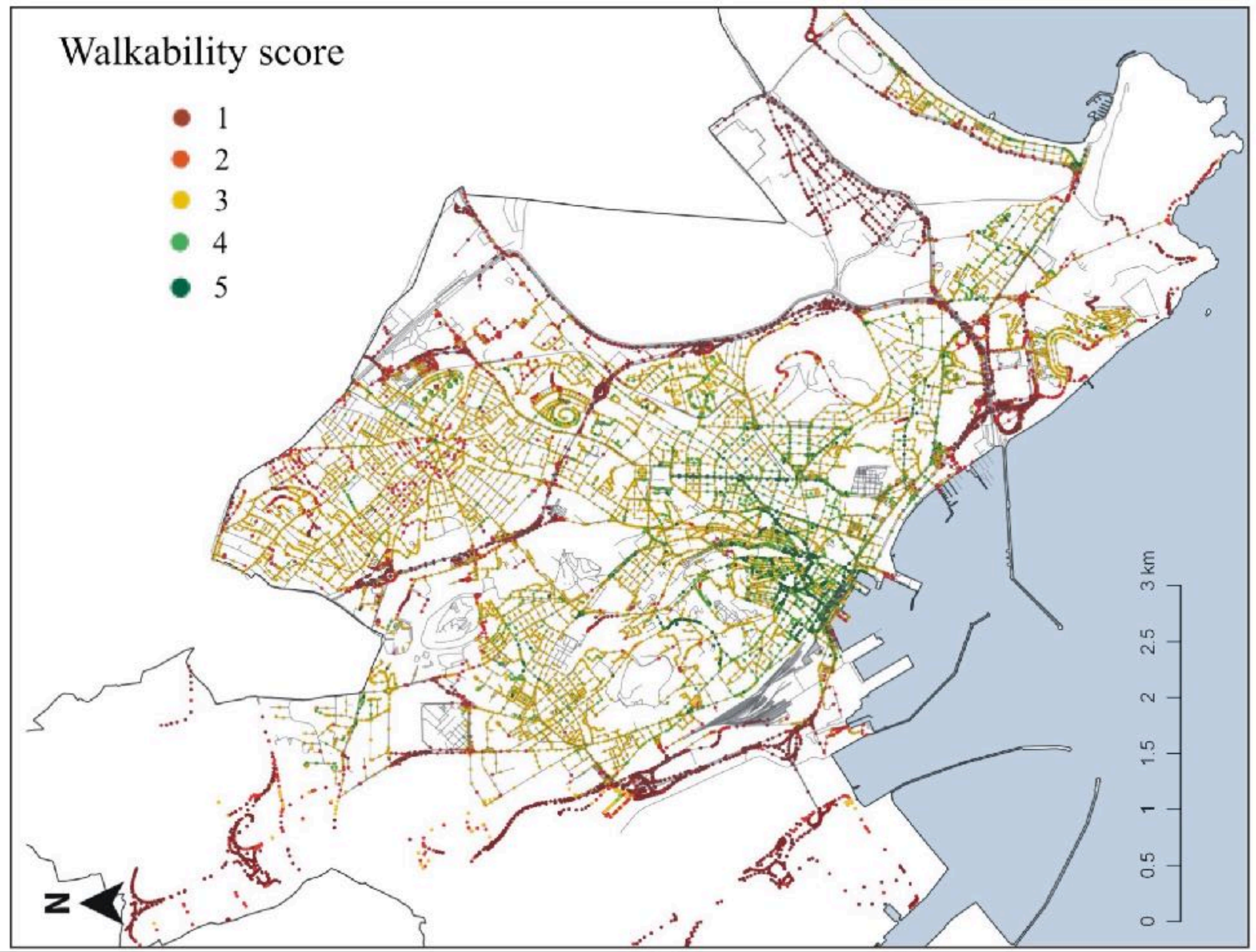
benjamin.beaucamp@ec-nantes.fr

Perception?



Safe
Dense
Clean
Tidy
Quiet
Spacious
Pleasant
Beautiful
Boring
Lively
Depressing

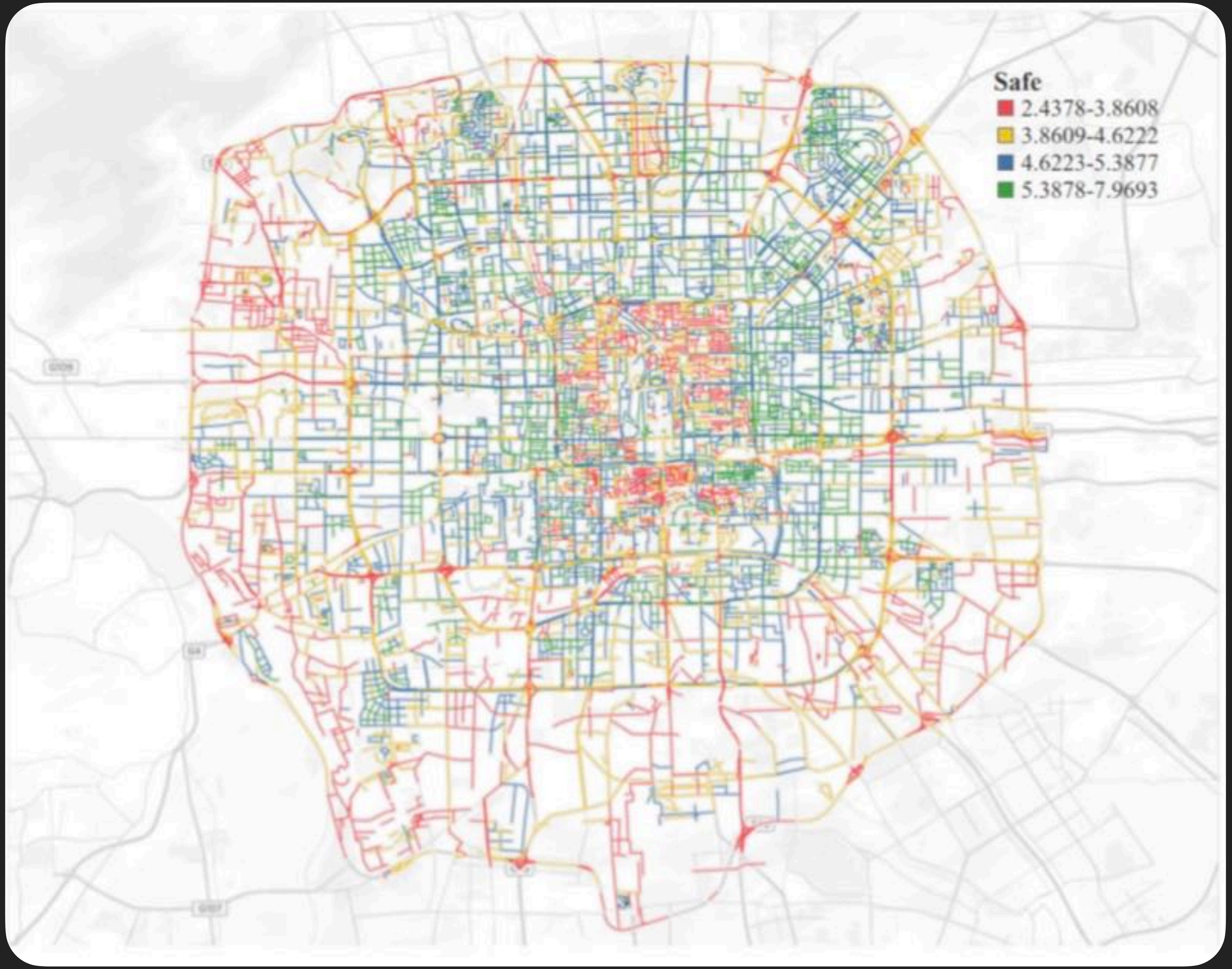
Perception maps

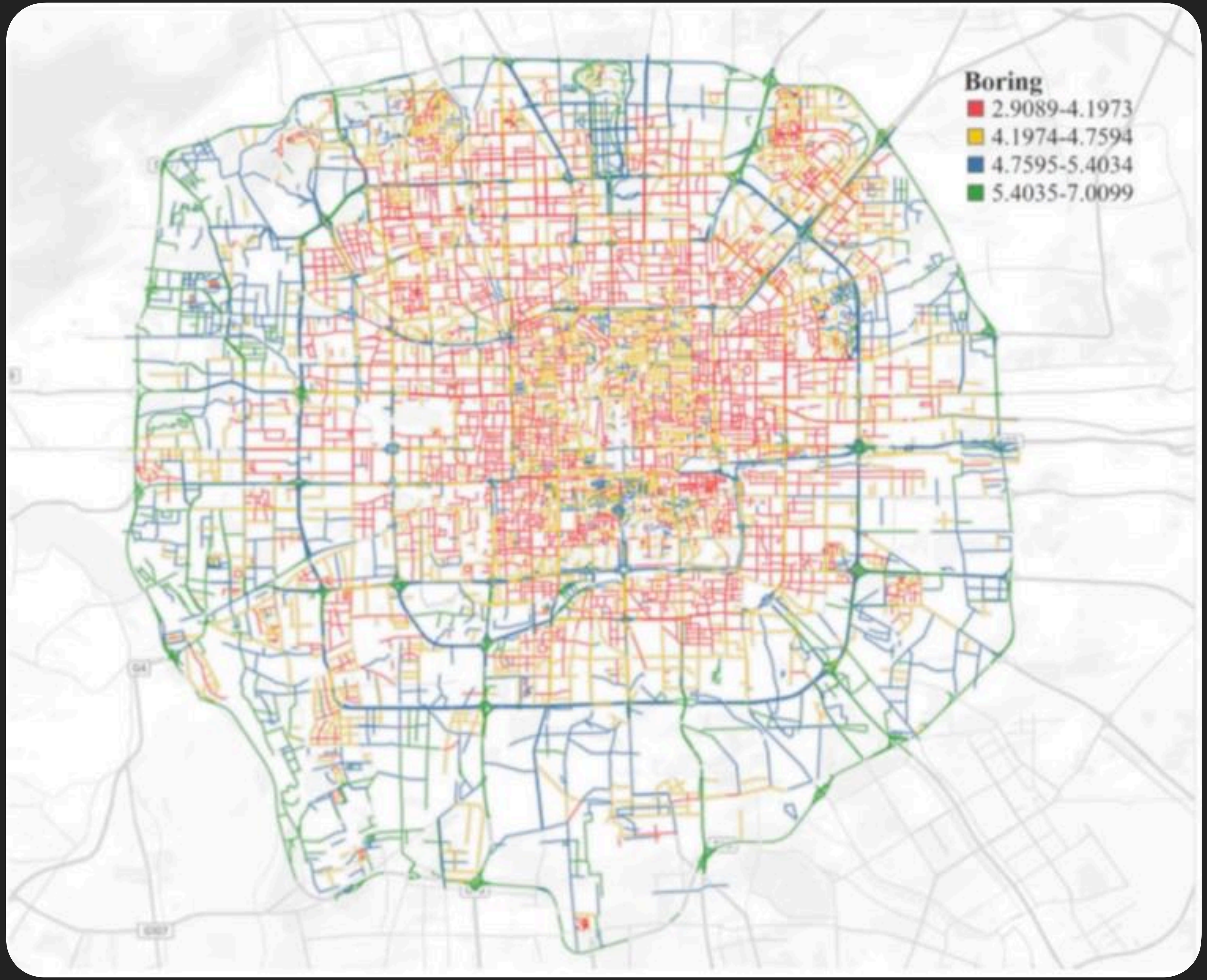


Blečić et al. (2018)

Perception maps

Street-level





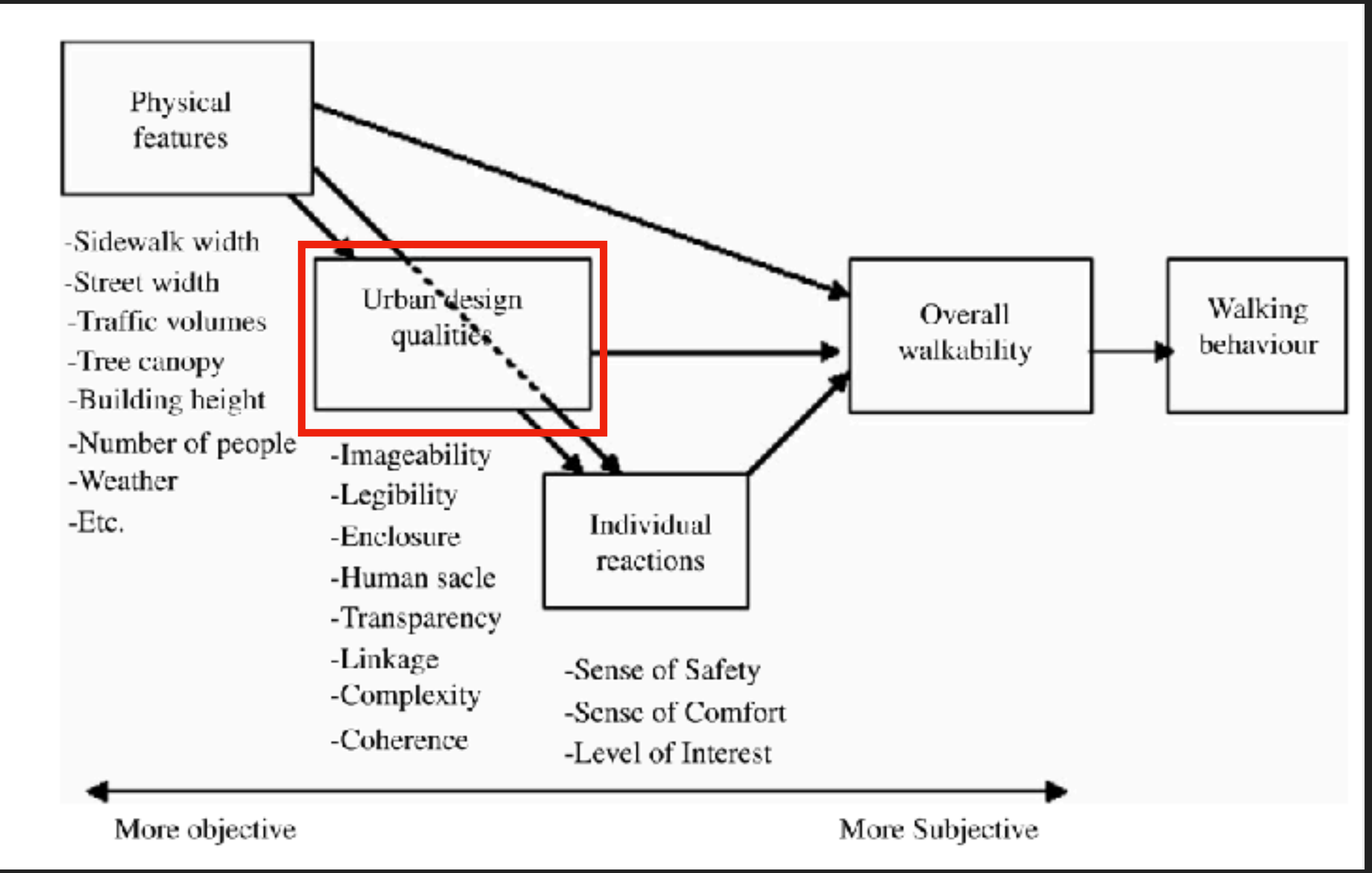
Ji et al. (2021)

Prediction of the perception

- Our goal is to qualify the perception of the urban space, from the point of view of a pedestrian.
- In the literature, the subjective qualities of the urban space are computed:
    - From physical features, e.g. Urban Design Qualities (Ewing et al., 2006)
    - By training NN with images and opinons of pedestrians, collected by crowdsourcing, e.g. *Dubey et al., 2016* or *Quercia et al. 2014*
- Potential usage:
    - Identify if an area is perceived negatively or positively
    - Identify *design elements* that are positively/negatively correlated with a given quality

Qualification by experts

Urban Design Qualities



Ewing and Handy (2009)

adaptability	distinctiveness	intricacy	richness
ambiguity	diversity	legibility	sensuousness
centrality	dominance	linkage	singularity
Clarity	enclosure	meaning	spaciousness
coherence	expectancy	mystery	territoriality
compatibility	focality.	naturalness	texture
comfort	formality	novelty	transparency
complementarity	human scale	openness	unity
complexity	identifiability	ornateness	upkeep
continuity	imageability	prospect	variety
contrast	intelligibility	refuge	visibility
deflection	interest	regularity	vividness
Depth	intimacy	rhythm	

Ewing and Handy (2009)

Qualification by experts

Urban Design Qualities

imageability

Imageability is the quality of a place that makes it distinct, recognizable, and memorable. A place has high imageability when specific physical elements and their arrangement capture attention, evoke feelings, and create a lasting impression.

What do the experts say?

"generic places with no character have no imageability"

"really imageable places are recognizable and memorable"

"distinct views can make an otherwise ordinary place very imageable"

"architecture that suggests importance, presence of historical buildings, and landmarks" are imageable

ask yourself "is the place unique?"

Streets filled with people, many signs, and strong landmarks make Times Square in New York City a very imageable place.

HIGH IMAGEABILITY

Few pedestrians, no street activity like outdoor dining, and no features that serve as landmarks make this street hardly distinguishable from others and thus not imageable.

LOW IMAGEABILITY

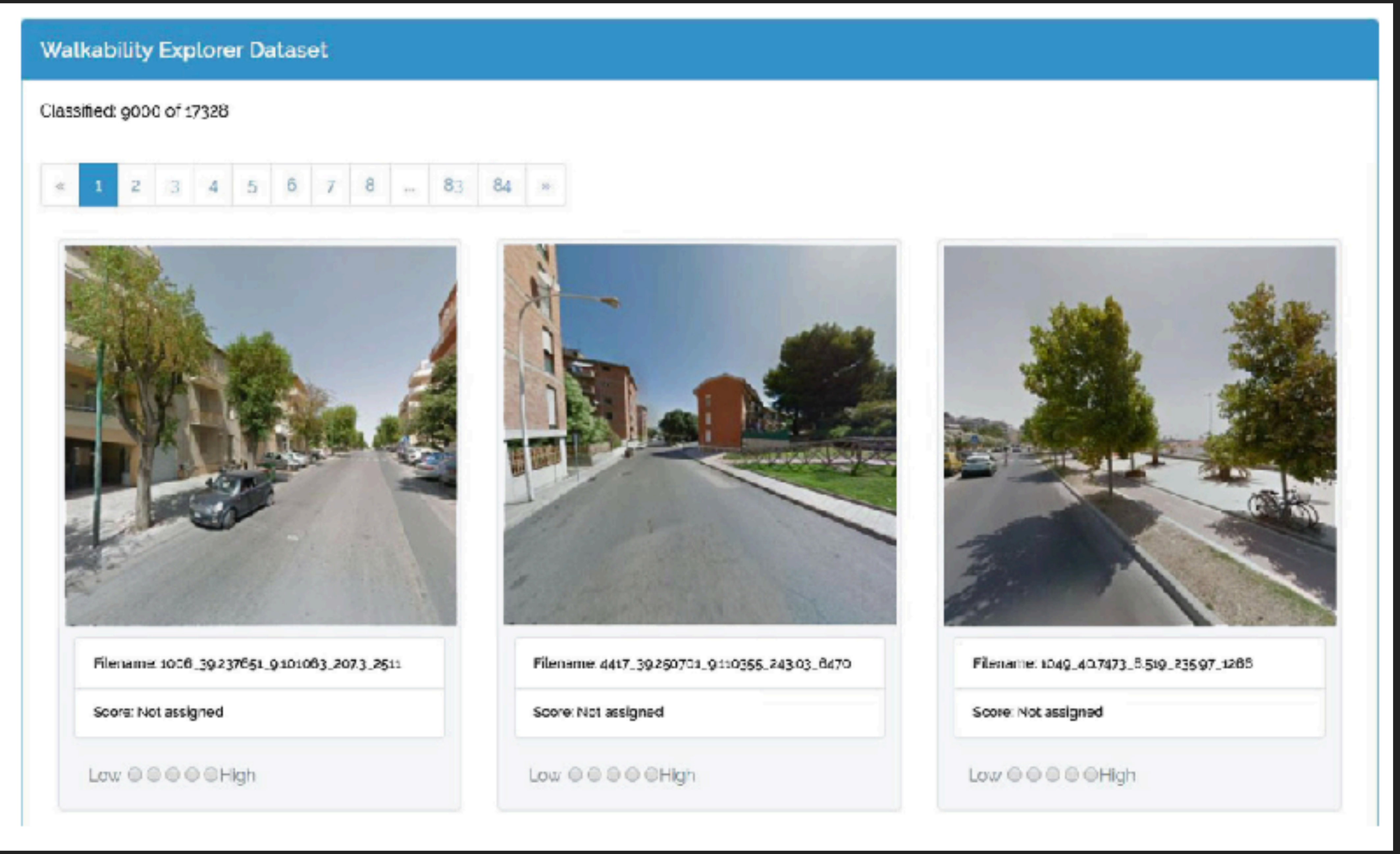
measuring urban design qualities scoring sheet	auditor		
street from	date & time		
step	recorded value	multiplier	(multiplier) x (recorded value)
imageability			
1. number of courtyards, plazas, and parks (both sides, within study area)		0.41	
2. number of major landscape features (both sides, beyond study area)		0.72	
3. proportion historic building frontage (both sides, within study area)		0.97	
4. number of buildings with identifiers (both sides, within study area)		0.11	
5. number of buildings with non-rectangular shapes (both sides, within study area)		0.08	
6. presence of outdoor dining (your side, within study area)		0.64	
7. number of people (your side, within study area) Walk through 1			
Walk through 2			
Walk through 3			
Walk through 4			
Total			
Total divided by 4		0.02	
8. noise level (both sides, within study area) Walk through 1			
Walk through 2			
Walk through 3			
Walk through 4			
Total			
Total divided by 4		-0.18	
		add constant	+2.44
	imageablity score		

Clemente et al. (2005)

Qualification by pedestrians

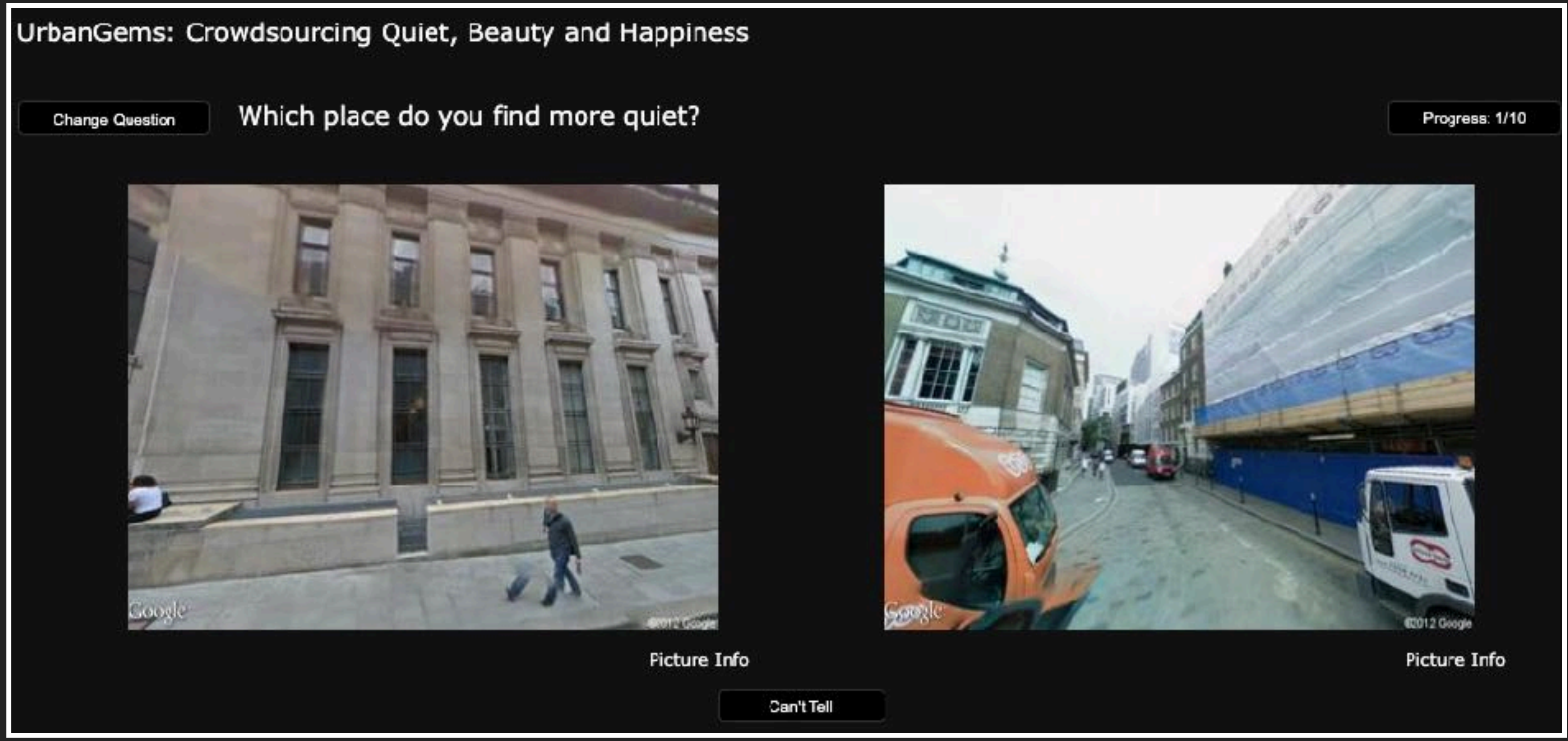
Crowdsourcing platforms

Absolute score



Blečić et al. (2018)

Pairwise comparisons



From urbangems.org

Qualification by pedestrians

Place Pulse 2.0 - Dubey et al. (2016)

110,000 images

1.1m annotations

80,000 users

3 years

Qualification of a place

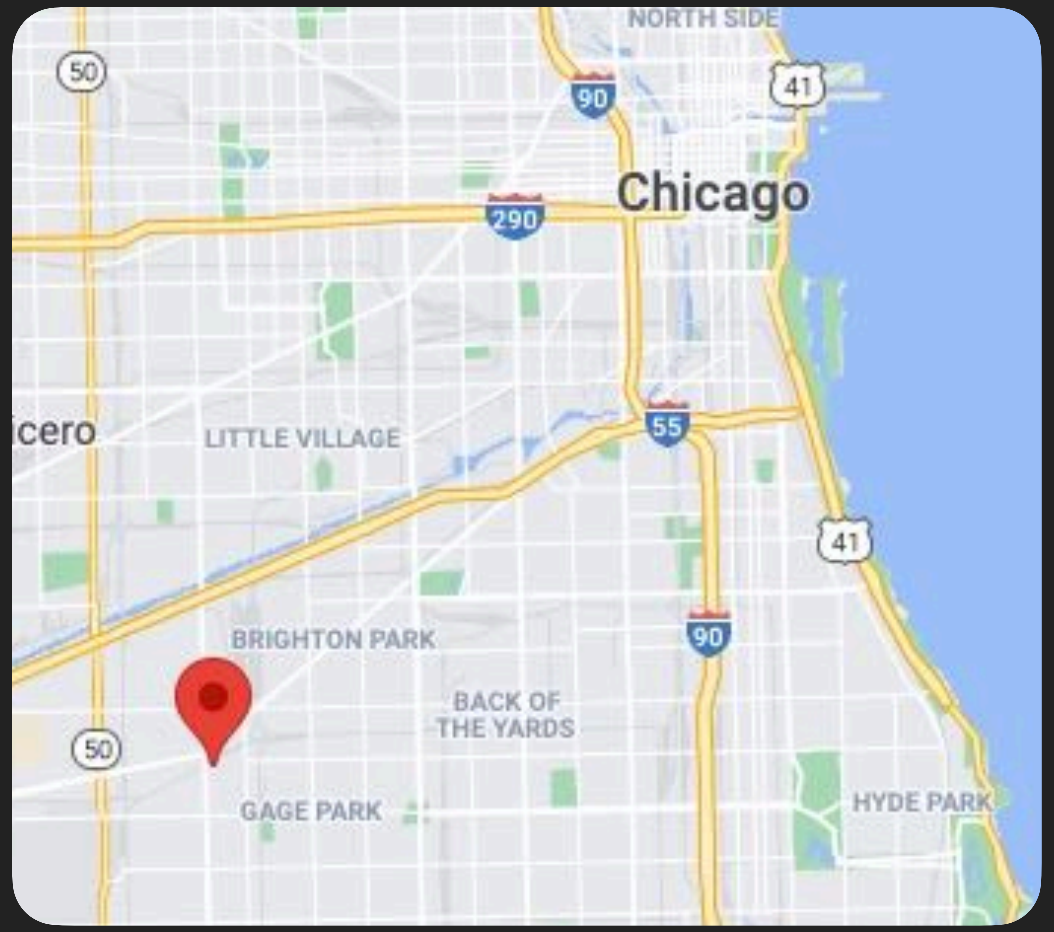
Pairwise comparison

Which place looks safer ?

Qualification of a place

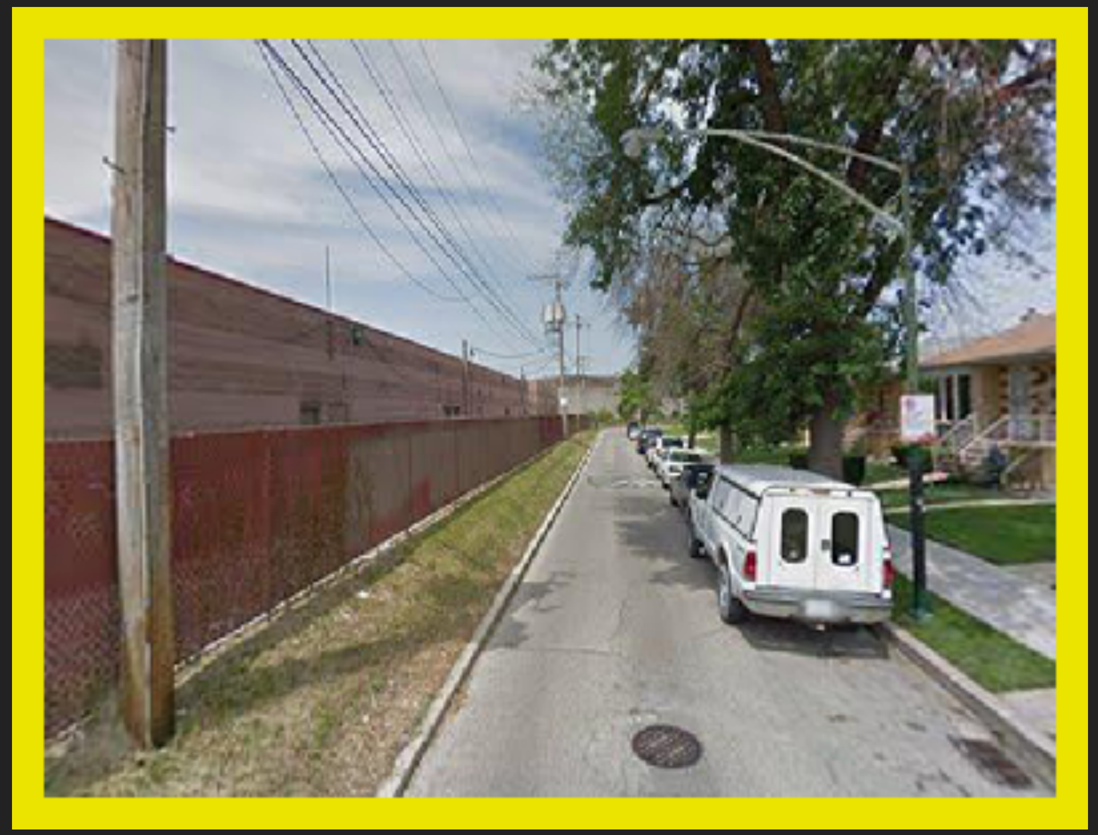
Using multiple images

360° panoramas

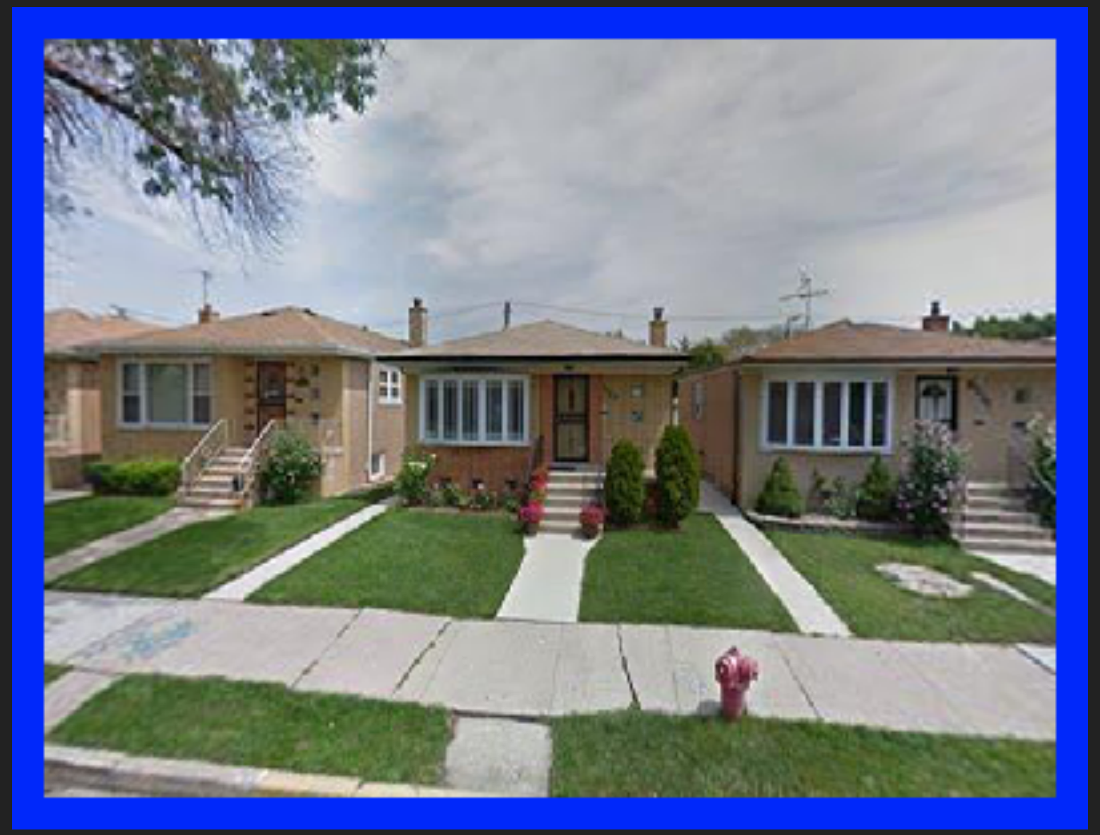


AAU crenau
ambiances
architectures
urbanités

0°



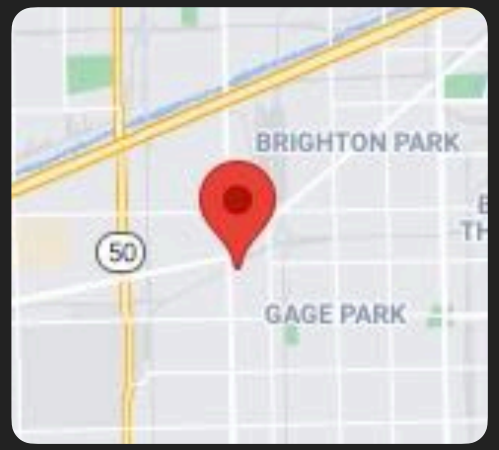
90°



180°

270°

Predicting perceptual scores



Average of the
4 images

safe	0.32
lively	0.24
beautiful	0.18
boring	0.73
depressing	0.80
wealthy	0.25

safe	0.99
lively	0.80
beautiful	0.83
boring	0.31
depressing	0.16
wealthy	0.87

safe	0.46
lively	0.44
beautiful	0.57
boring	0.72
depressing	0.51
wealthy	0.46

safe	0.17
lively	0.12
beautiful	0.13
boring	0.80
depressing	0.93
wealthy	0.17

safe	0.49
lively	0.40
beautiful	0.43
boring	0.67
depressing	0.60
wealthy	0.44

But what if we choose different viewpoints ?

0° 90° 180° 270° 40° 130° 220° 310°

THE WHOLE IS OTHER THAN THE SUM OF ITS PARTS: SENSIBILITY ANALYSIS OF 360° URBAN IMAGE SPLITTING

B. Beaucamp, T. Leduc, V. Tourre, M. Servières - 2022

The International Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives
https://doi.org/10.5194/isprs-annals-V-4-2022-33-2022

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

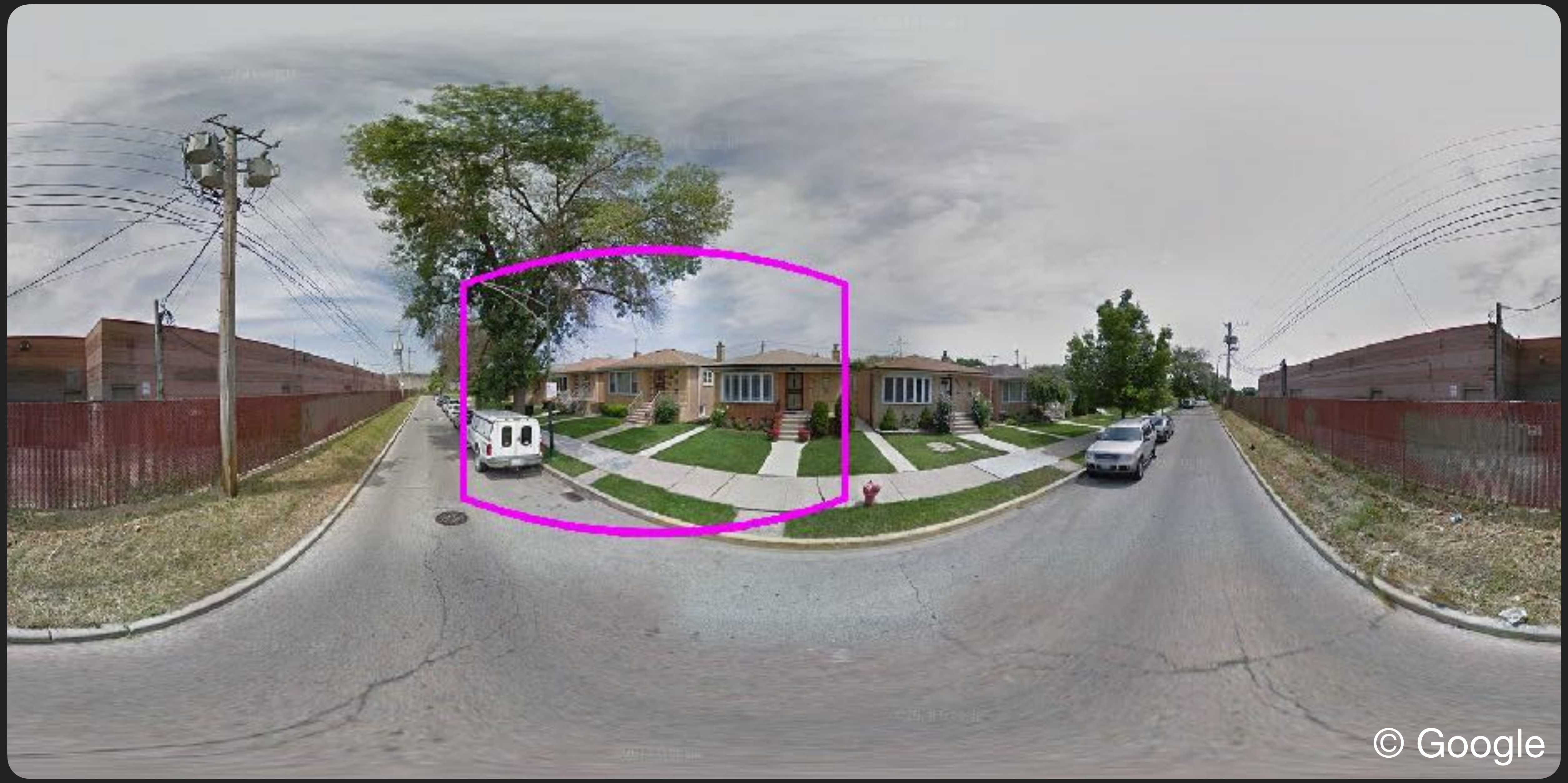
Sliding viewport

Sliding viewport

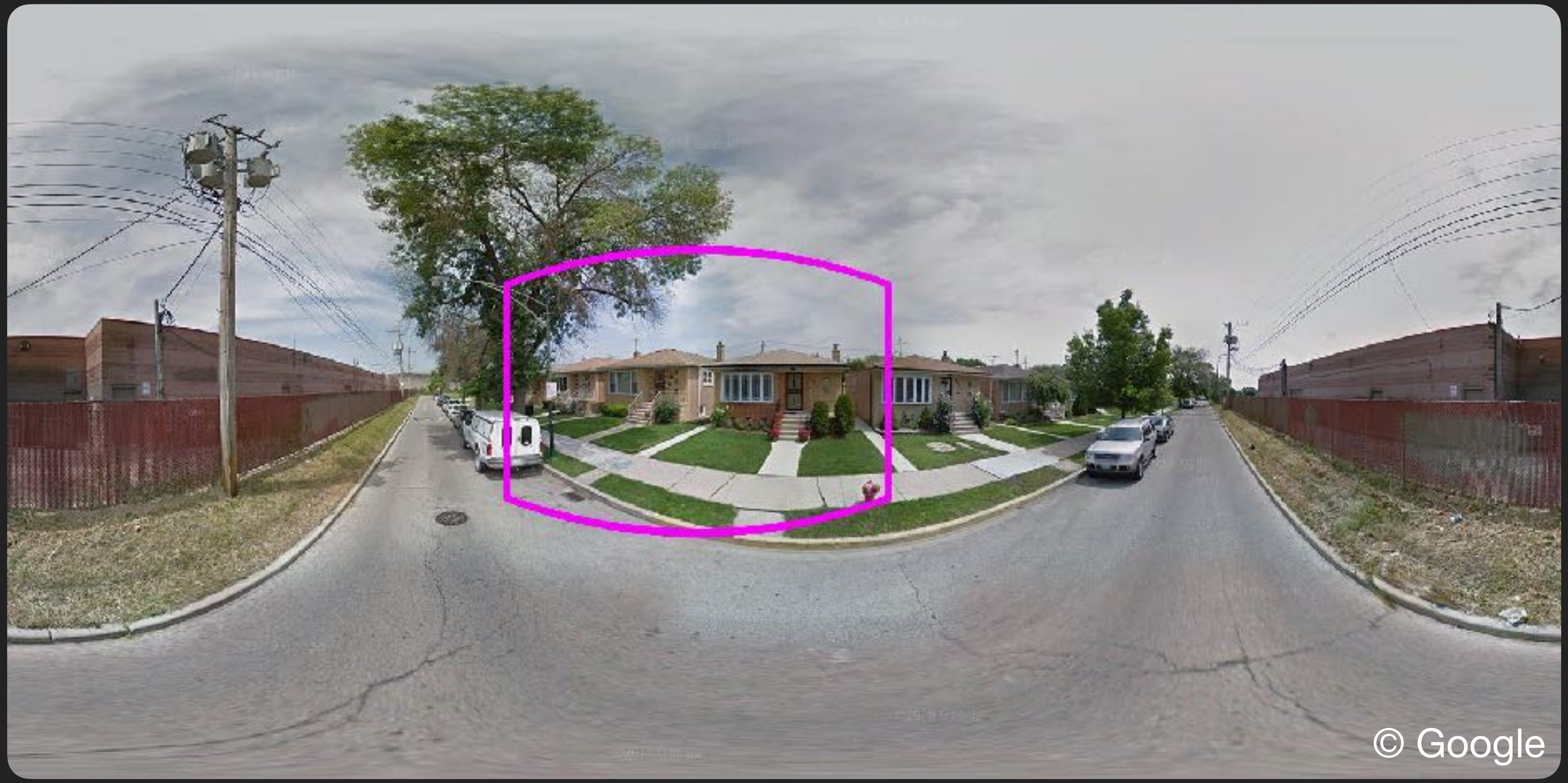
Sliding viewport

Sliding viewport

Sliding viewport



Sliding viewport



Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

Sliding viewport

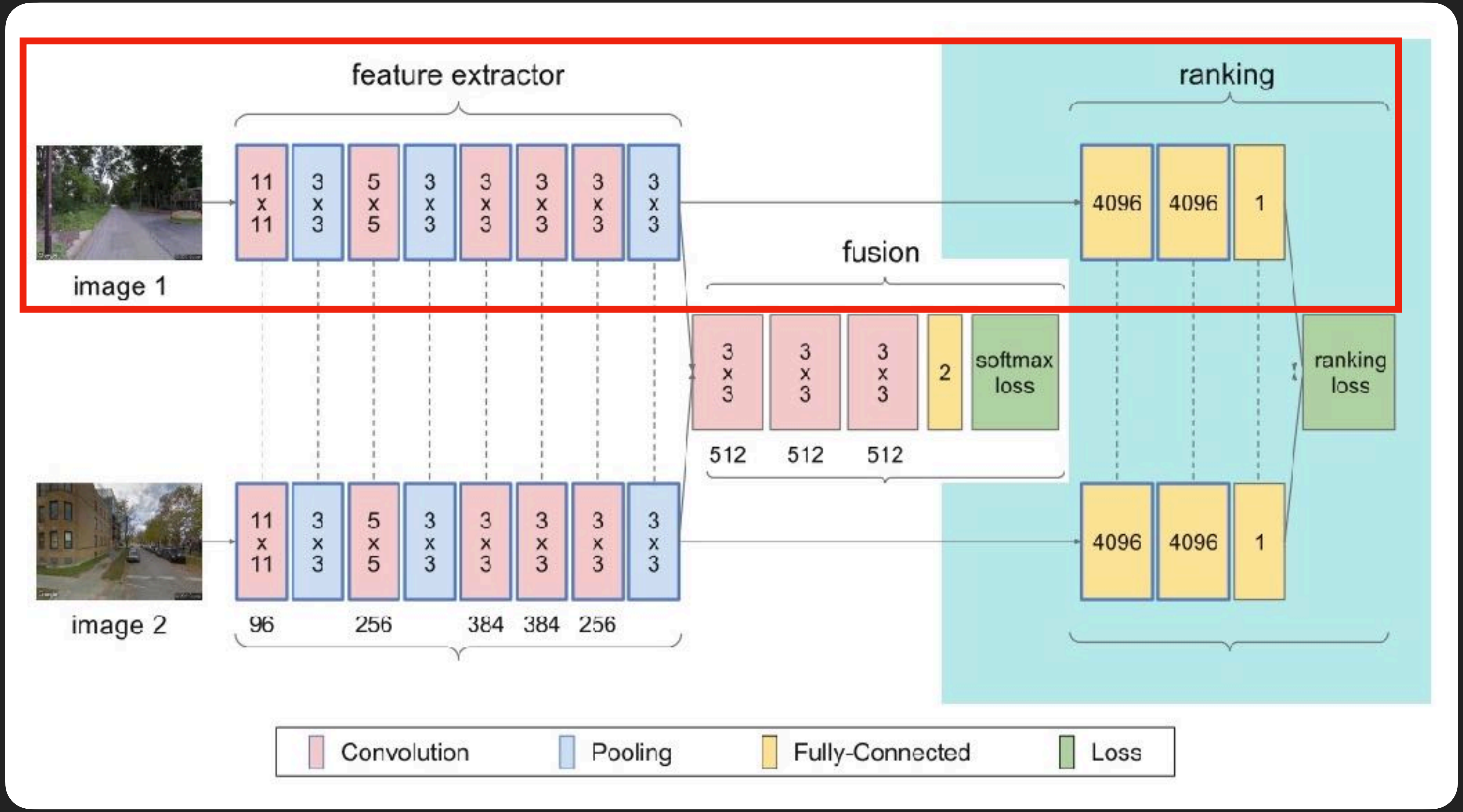
Sliding viewport

Sliding viewport

Sliding viewport

Prediction of the perception

Ranking StreetScore-CNN (RSSCNN)



Dubey et al. (2016)

- 1 network for each quality
  - → 6 independent networks
- 62.2% - 69.8% accuracy

Prediction of the perception

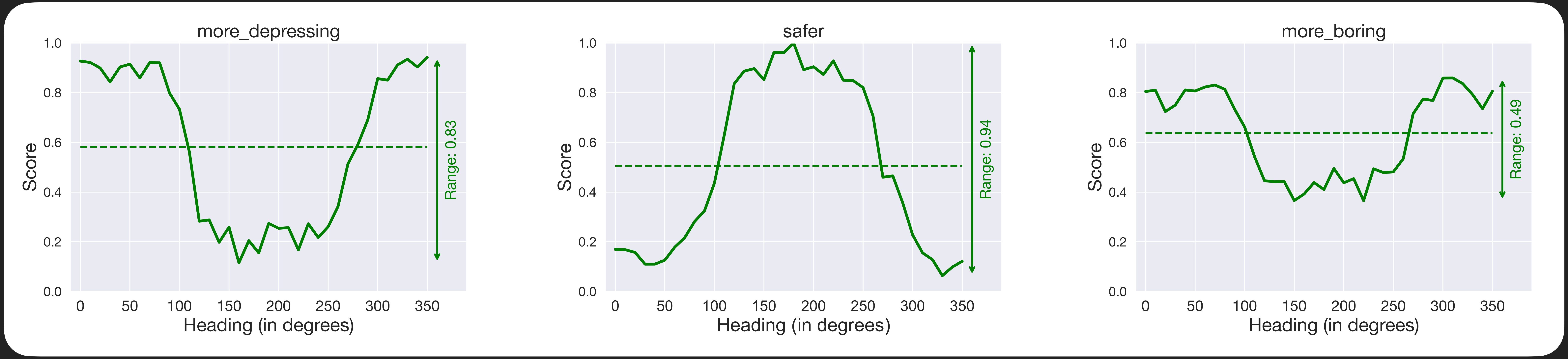
Extending the PP2 dataset

Image in the PP2 dataset

Full 360° panorama retrieved on Google Street View

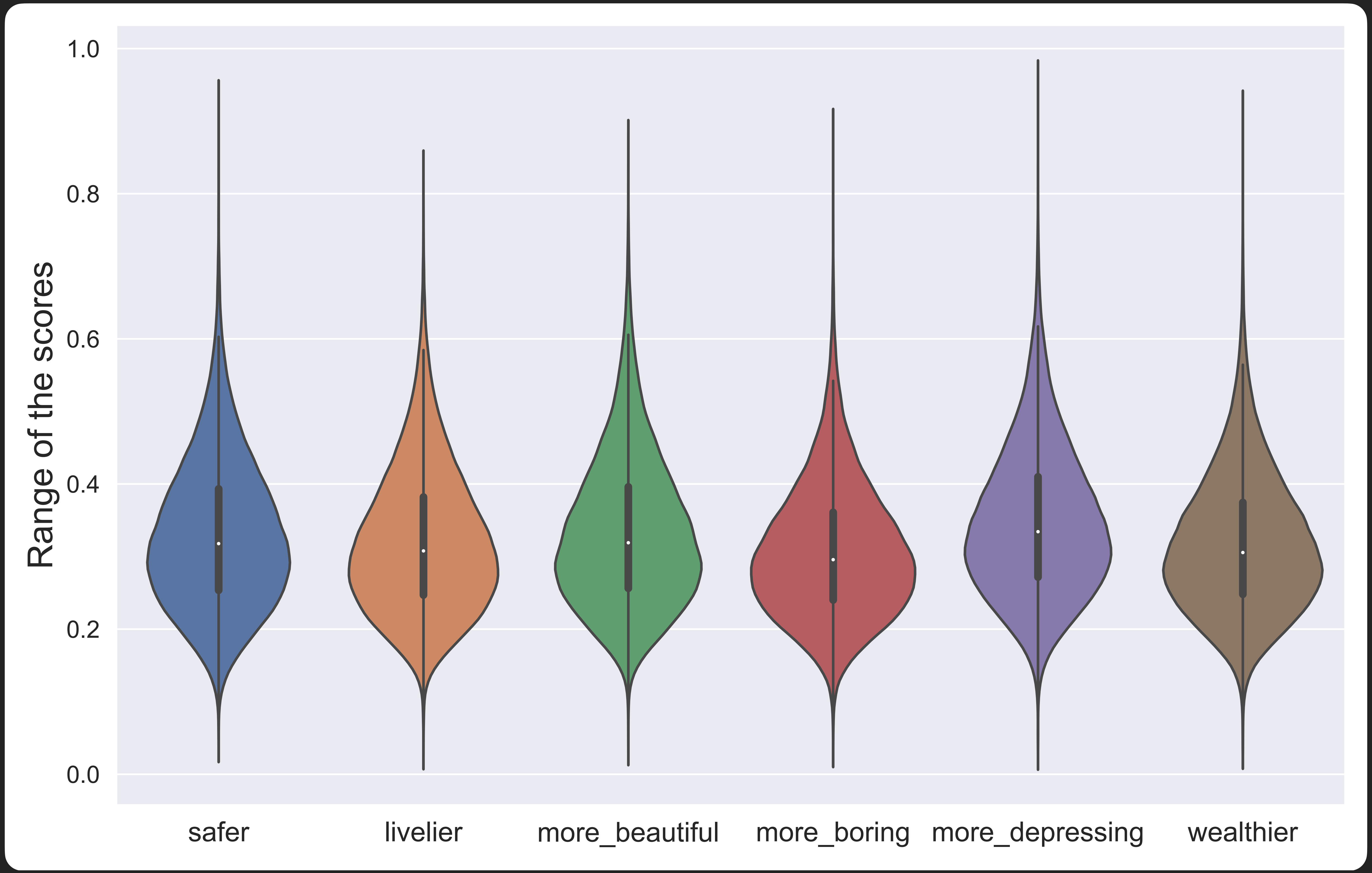
In total we retrieved ~100,000 panoramas, for a total of 3.6m perspective images and 21.6m scores after inference

Distribution of the scores on a panorama



Results (1)

Distribution of the range of the scores on a panorama

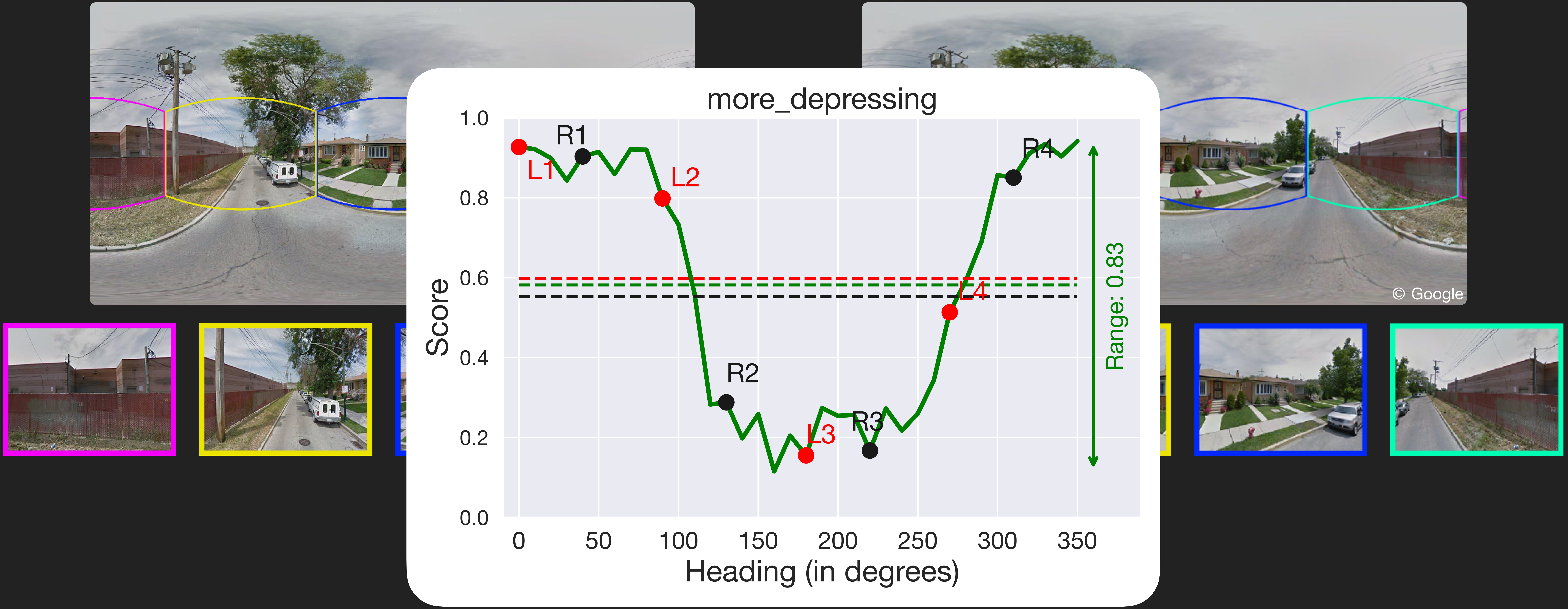


Results (2)

Impact of the panorama cut-out

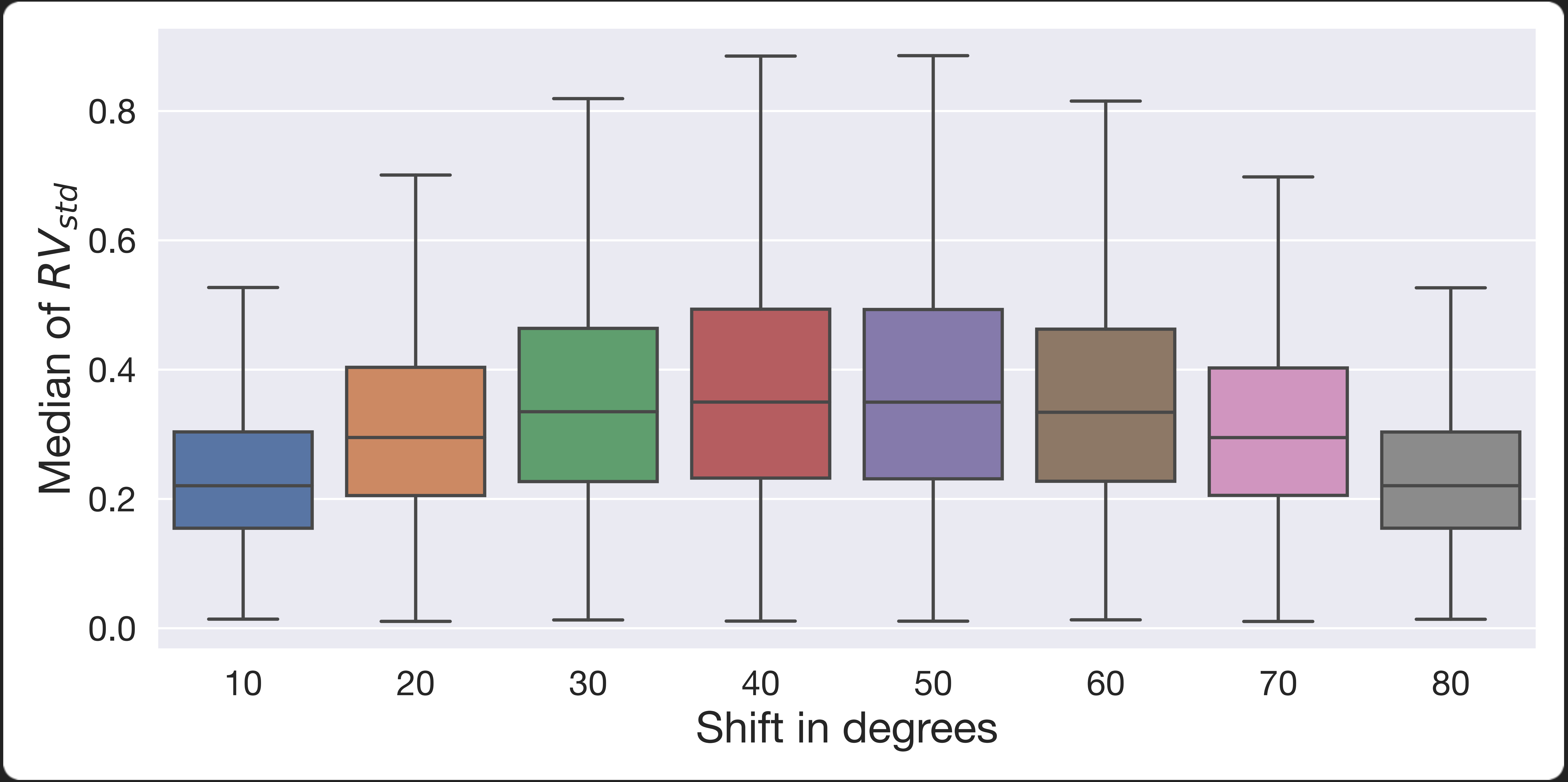
Reference

Shifted



Results (2)

Impact of the panorama cut-out



$$RV_{std} = \frac{|\mathrm{std}_{\mathrm{ref}} - \mathrm{std}_{\mathrm{shifted}}|}{\mathrm{std}_{\mathrm{ref}}}$$

AAU crenau
ambiances
architectures
urbanités

Conclusion

- The scores at a panorama-level have high variability.
- Scores are highly dependent on the main direction of the split

Future work

- Find a better way to aggregate the scores at a given location
- Take into account the spatial / temporal dependencies between the viewpoints
- Take full advantage of 360° images

Crowdsourcing perception on panoramas

Crowdsourcing annotations

Motivations

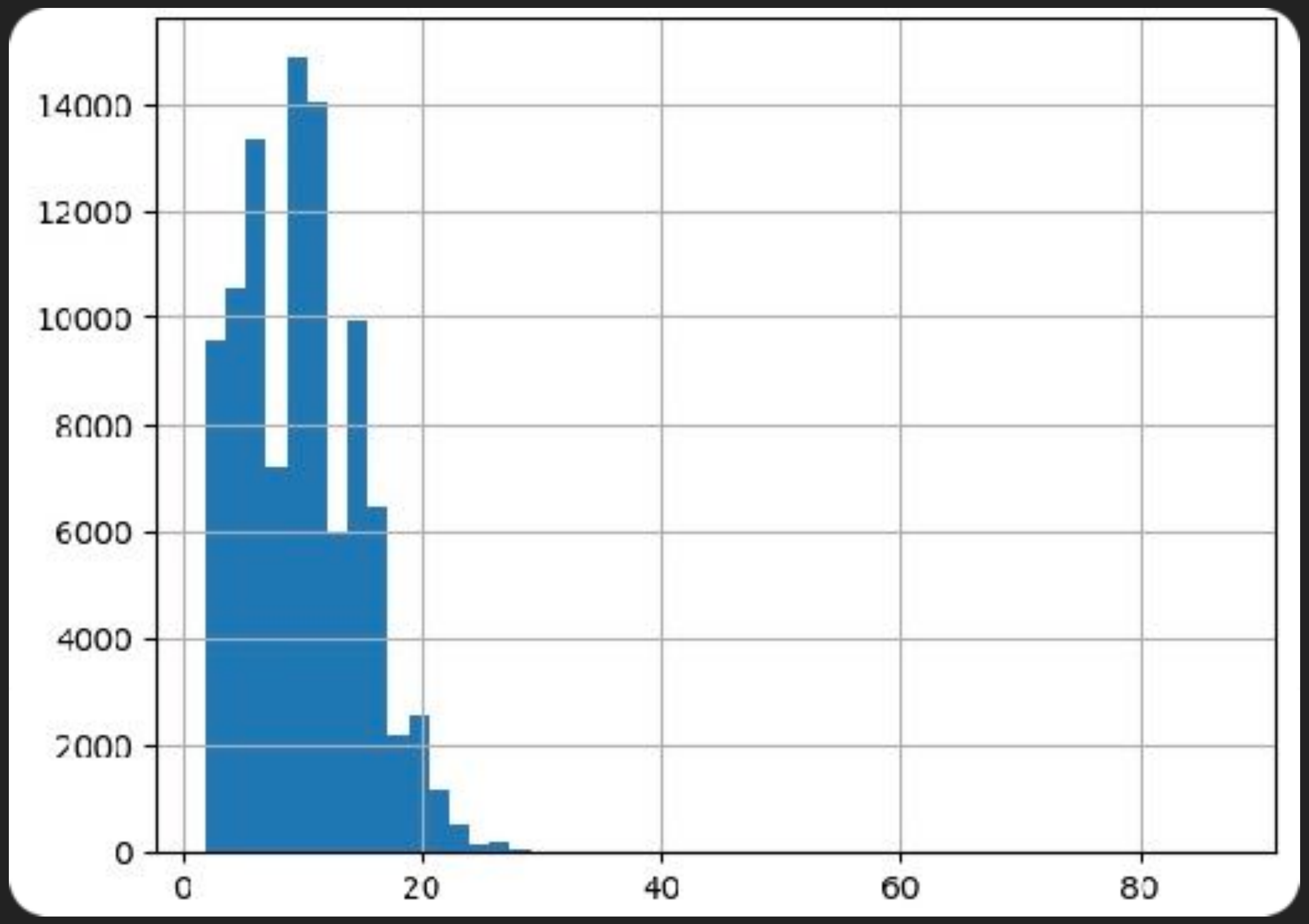
(a) Statistics on Images

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

(b) Statistics on Pairwise Comparisons (PC)

Question	#PC	#Per-image PC
Safe	370,134	7.67
Lively	268,494	5.52
Beautiful	166,823	3.46
Wealthy	137,688	2.87
Depressing	114,755	2.47
Boring	111,184	2.40
Total	1,169,078	16.73

Dubey et al. (2016)



Number of pairwise comparisons for “safer” in PP2

- High number of images…
- …but low number of annotations per image
- No information about the participants
- Only 90° FOV images

Crowdsourcing annotations

Designing a web platform to collect data

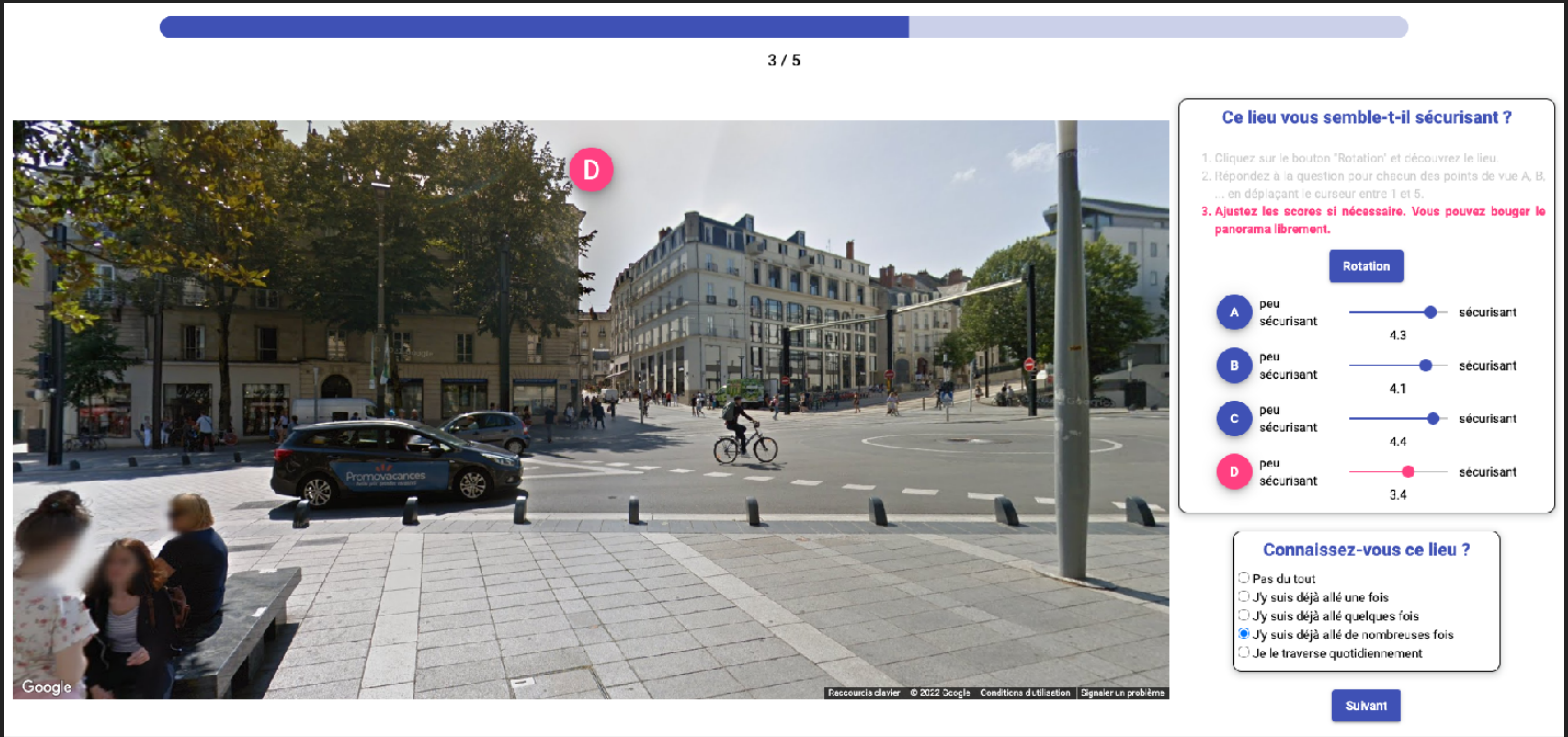
What we want:

- Annotations on 360° images (panoramas)
- Socio-demographic data about the participants
- A large amount of annotations:
  - Minimum number of annotations for each image for robust statistics
  - A diverse set of panoramas annotated

Crowdsourcing annotations on 360° images

UP2 - http://up2.huma-num.fr

Panorama task



Crowdsourcing annotations on 360° images

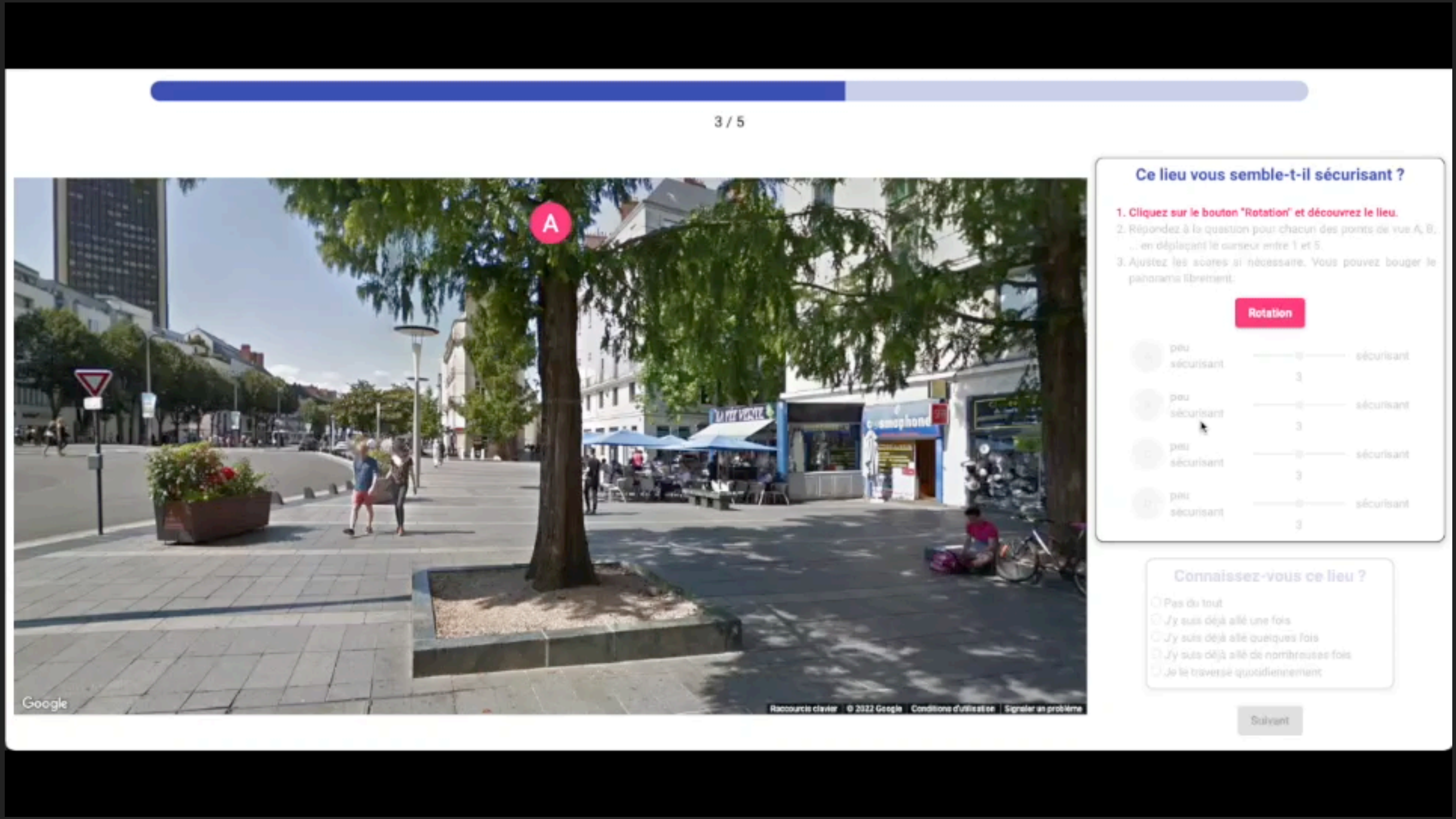
UP2 - http://up2.huma-num.fr

Image task

AAU crenau
ambiances
architectures
urbanités

Crowdsourcing annotations on 360° images

UP2 - http://up2.huma-num.fr



Thank you for listening

http://up2.huma-num.fr

✉ benjamin.beaucamp@ec-nantes.fr

References

- Clemente, O., Ewing, R., Susan, H., & Brownson, R. (2005).
  Measuring urban design qualities: An illustrated field manual.
  NJ: Robert Wood Johnson Foundation.

- Blečić, I., Cecchini, A., & Trunfio, G. A. (2018).
  Towards automatic assessment of perceived walkability.
  Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 10962 LNCS, 351–365. https://doi.org/10.1007/978-3-319-95168-3_24

- Dubey, A., Naik, N., Parikh, D., Raskar, R., & Hidalgo, C. A. (2016).
  Deep learning the city: Quantifying urban perception at a global scale.
  Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 9905 LNCS, 196–212. https://doi.org/10.1007/978-3-319-46448-0_12

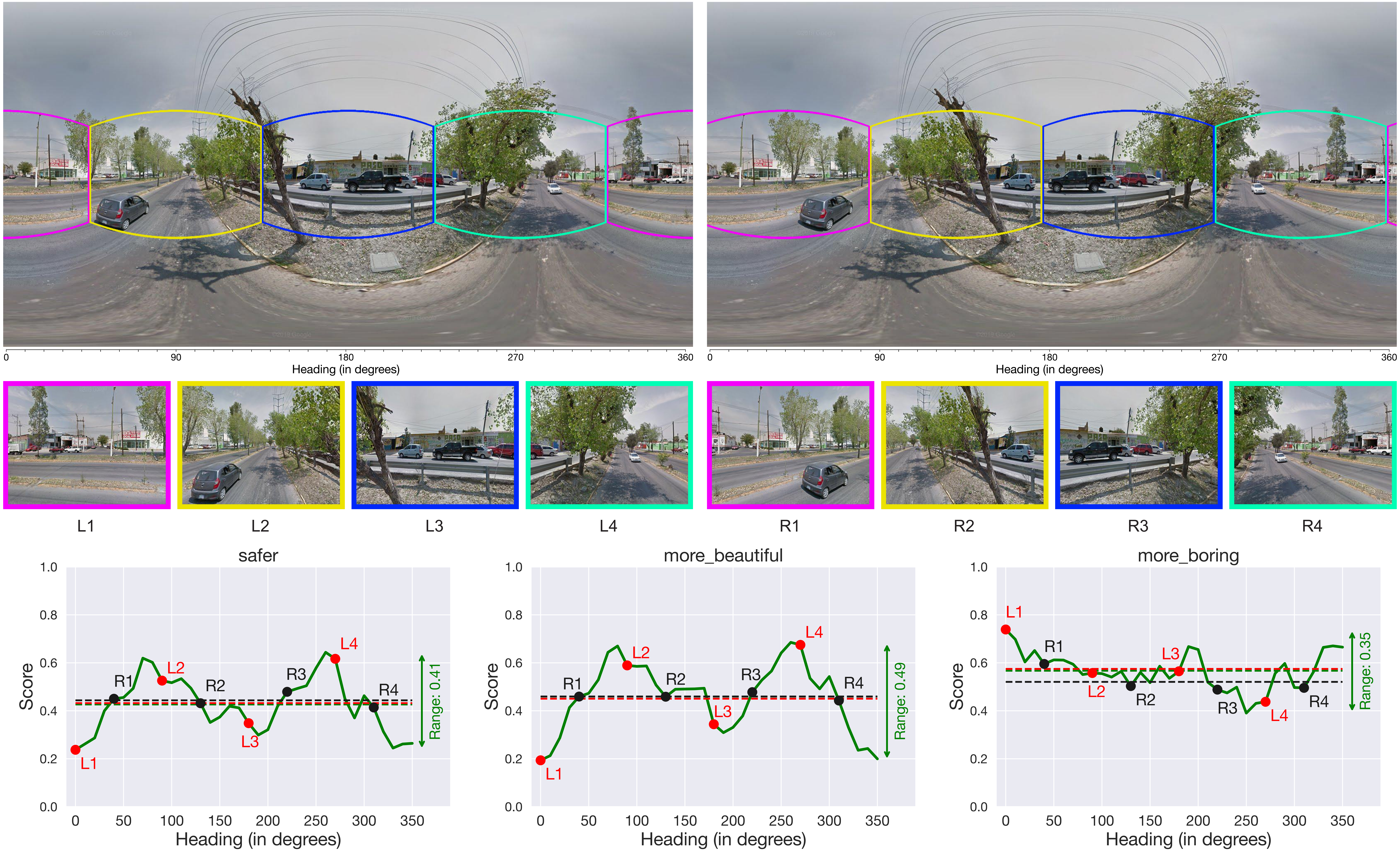
- Ewing, R., & Handy, S. (2009).
  Measuring the unmeasurable: Urban design qualities related to walkability.
  Journal of Urban Design, 14(1), 65–84. https://doi.org/10.1080/13574800802451155

- Quercia, D., O'Hare, N., & Cramer, H. (2014).
  Aesthetic capital: What makes london look beautiful, quiet, and happy?
  Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW, 945–955. https://doi.org/10.1145/2531602.2531613

- Ji, H., Qing, L., Han, L., Wang, Z., Cheng, Y., Peng, Y., … Kainz, W. (2021).
  A New Data-Enabled Intelligence Framework for Evaluating Urban Space Perception.
  ISPRS International Journal of Geo-Information 2021, Vol. 10, Page 400, 10(6), 400. https://doi.org/10.3390/ijgi10060400

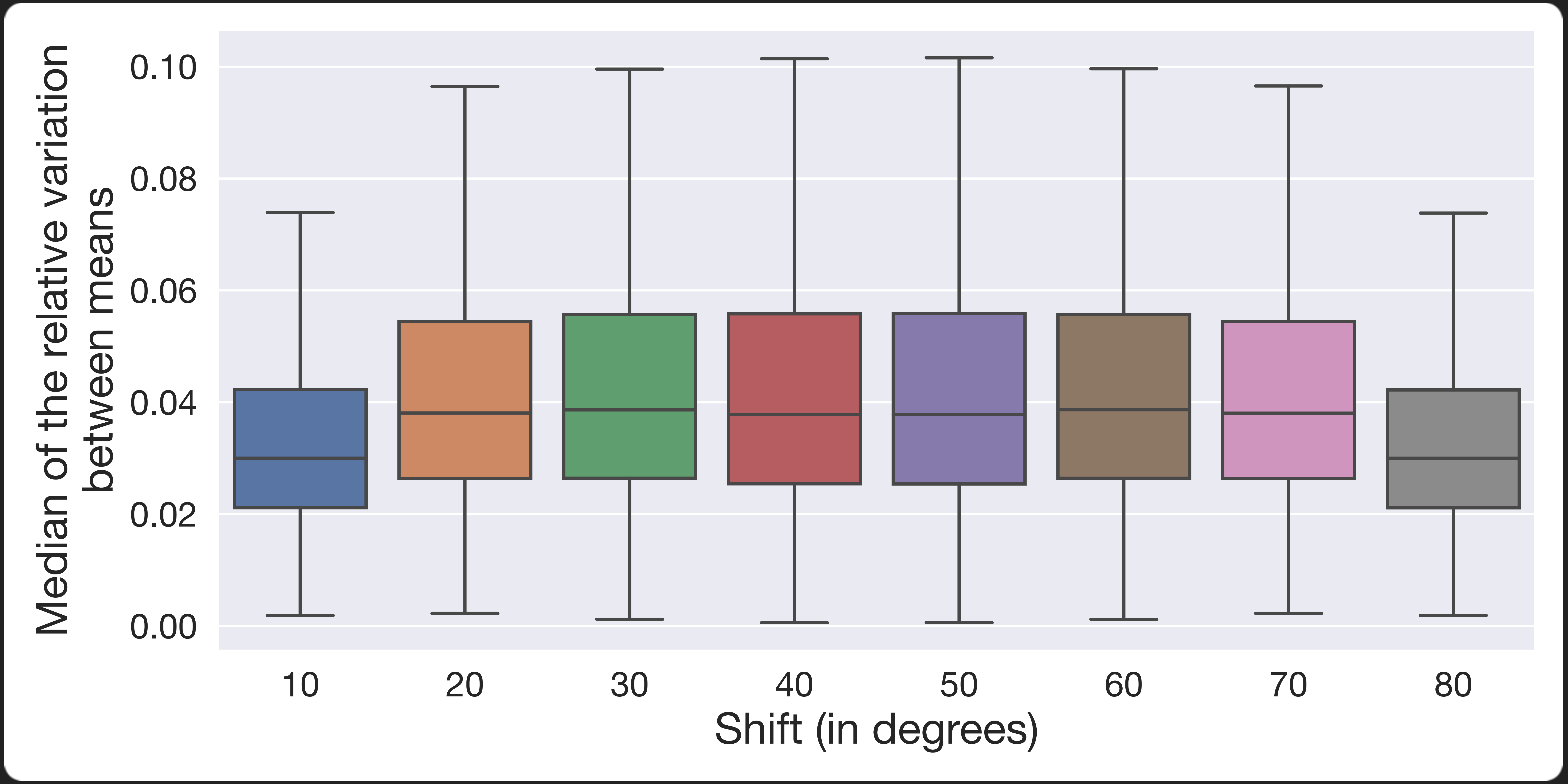
Appendices

safer
more_depressing
more_boring
Score
Heading (in degrees)
Range: 0.94
Range: 0.83
Range: 0.49
L1
L2
L3
L4
R1
R2
R3
R4



0
90
180
270
360
Heading (in degrees)
L1
L2
L3
L4
R1
R2
R3
R4
safer
more_beautiful
more_boring
Score
Heading (in degrees)
Range: 0.41
Range: 0.49
Range: 0.35

Impact of the split on the mean score



Example: a street in Nantes, France

Passive crowdsourcing

Social networks

Analyse de sentiments:

- Utilisation d’un dictionnaire existant
- Topic modeling

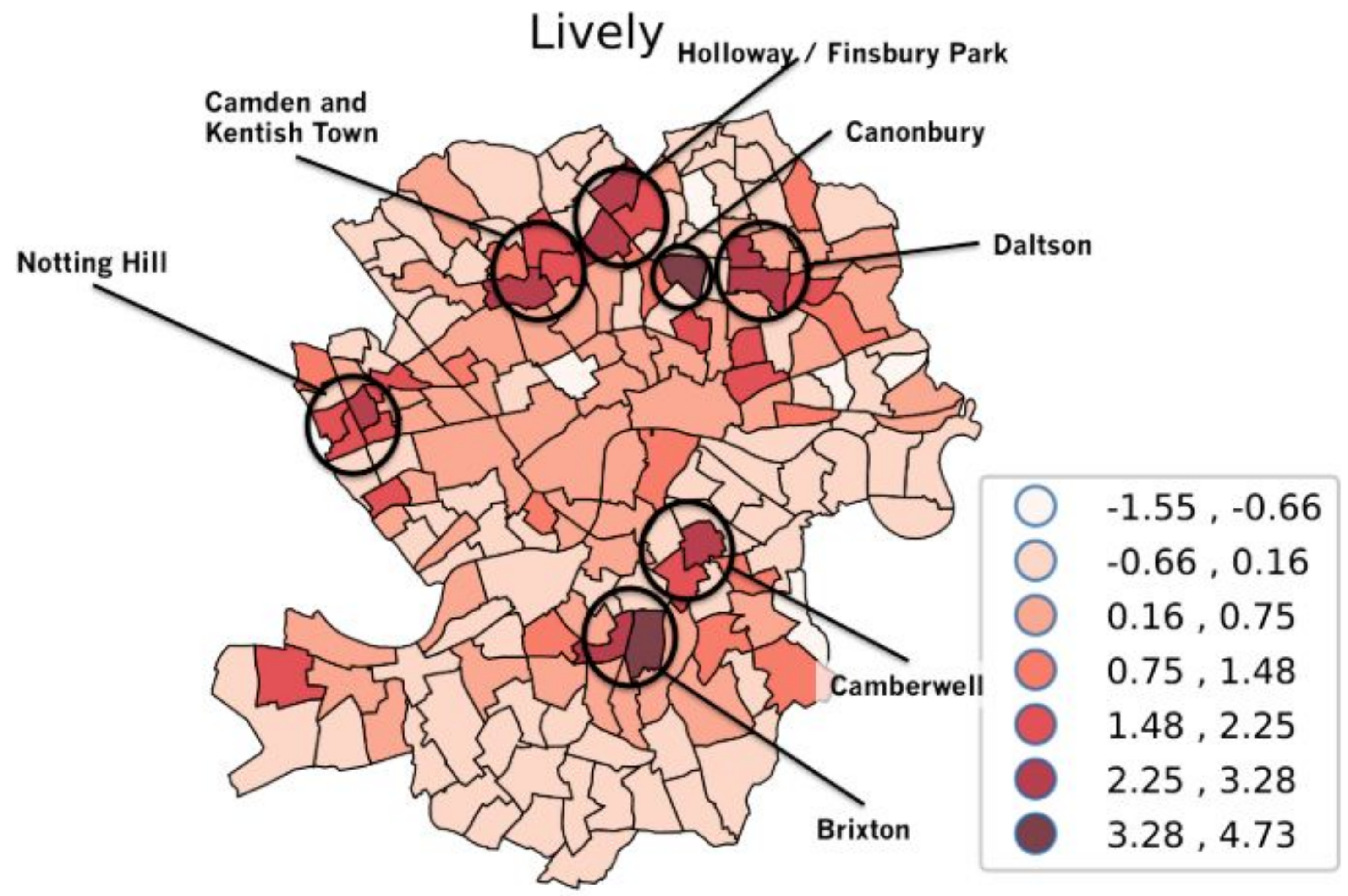
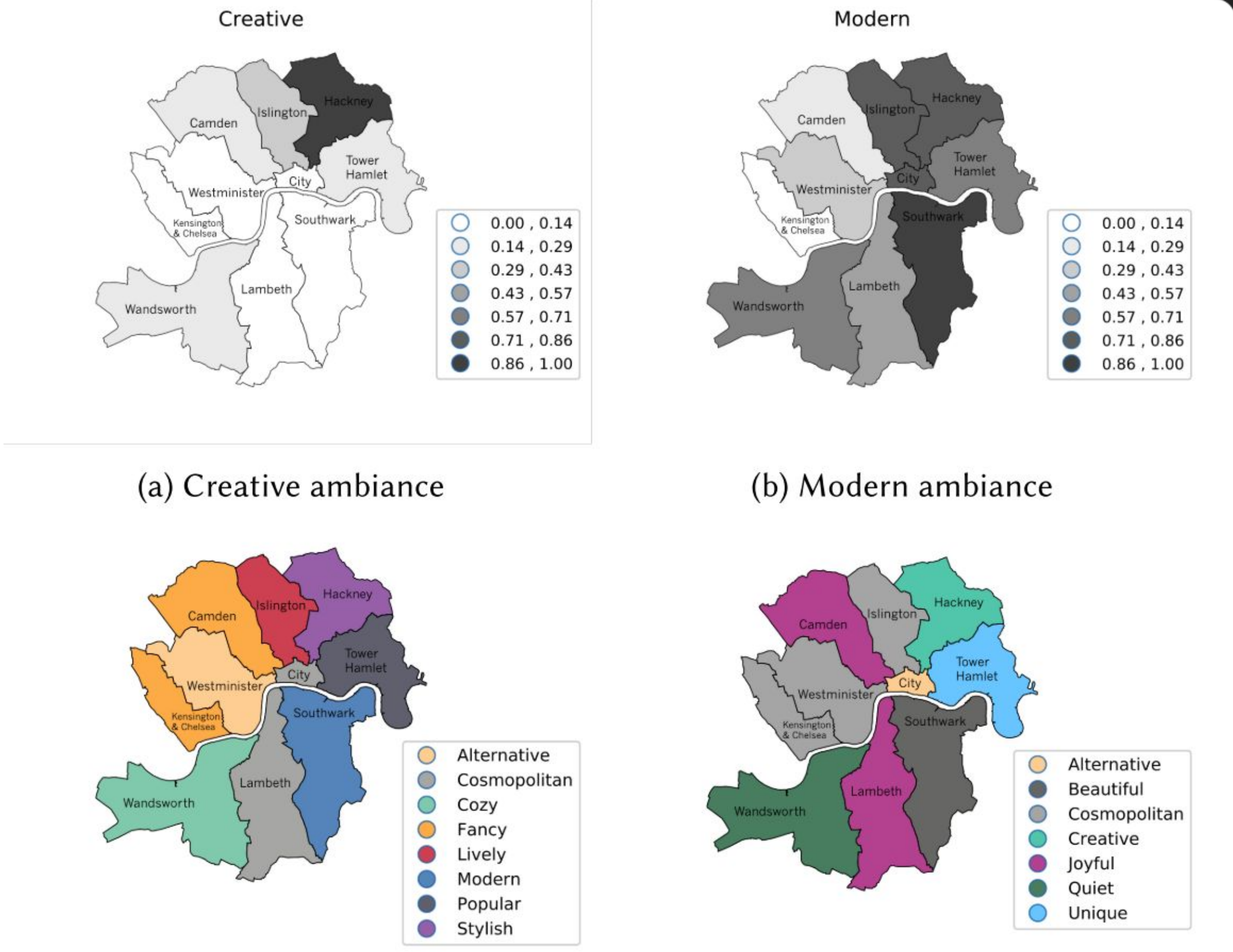


Fig. 3. The most and the least ‘lively’ wards in central London.

Redi al. (2018)



(a) Creative ambiance

(b) Modern ambiance

(c) The most prominent ambiance.

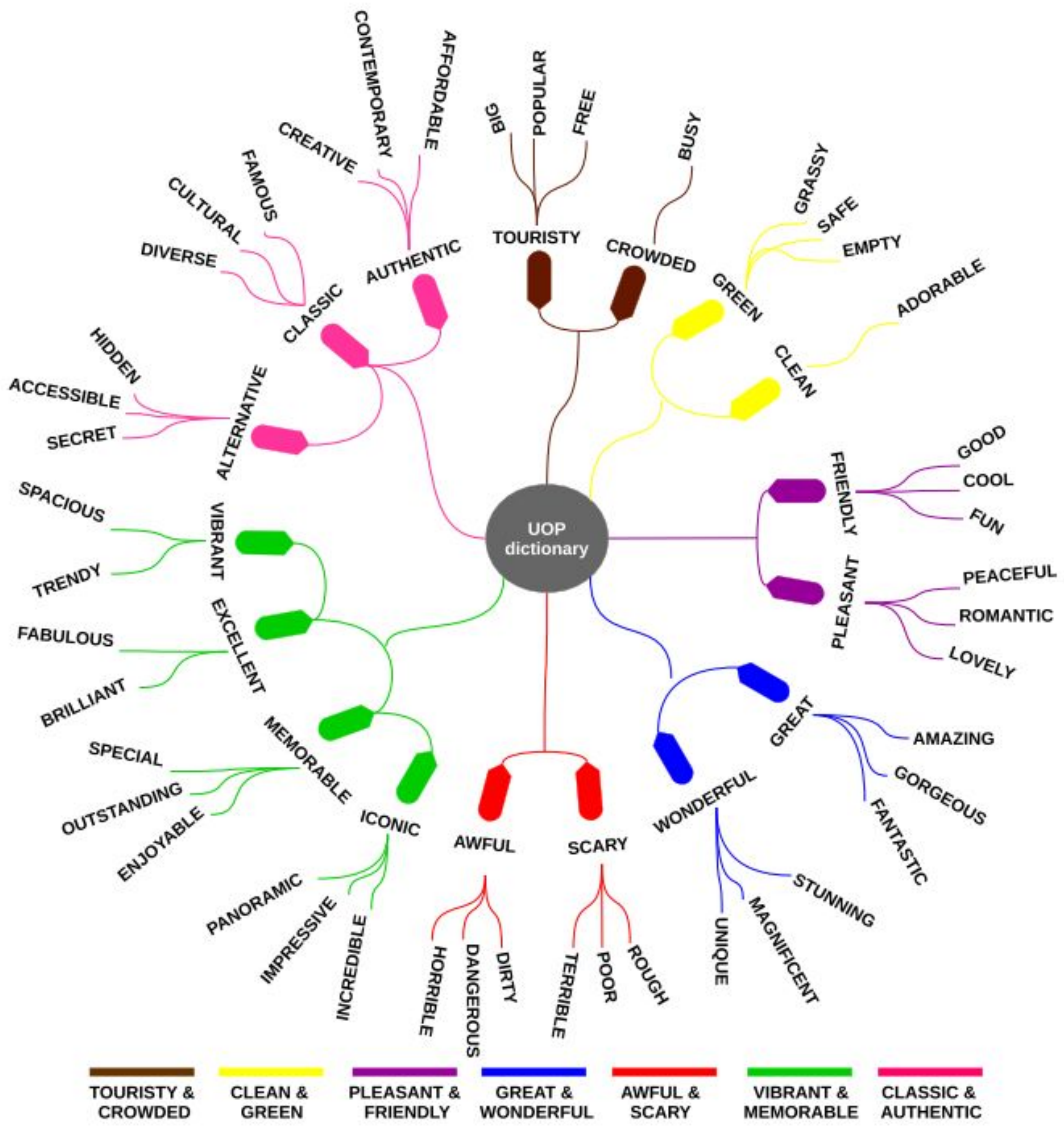
(d) The second most prominent ambiance.

Redi al. (2018)

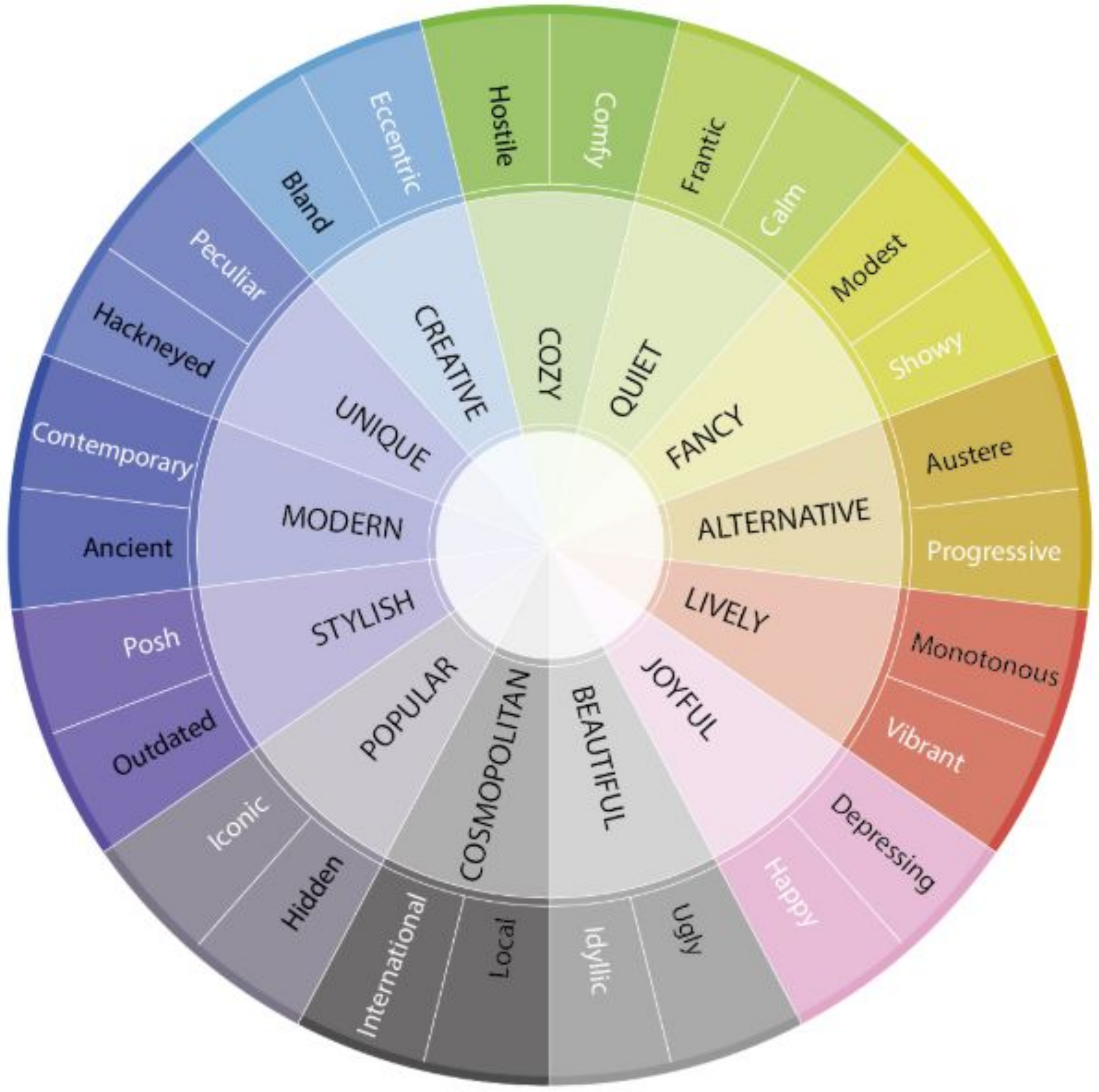
Passive crowdsourcing

Dictionaries

Google Places +
Foursquare



Santos et al. (2019)



Redi al. (2018)

Sources multiples: livres, tags Airbnb, vocabulaire sur les ambiances