FGV EMAp

IEEE BIG DATA 2025

UrbanPhysicalDisorder-4K

Understanding Urban Perception **via Counterfactuals** and Street View Signs of **Physical Disorder**

Felipe Moreno-Vera

Andres De-la-Puente

Jorge Poco

Fundação Getulio Vargas / Visual Data Science Lab

www.visualdslab.com

V-DS

CAPES
Coordenação de Aperfeiçoamento de Pessoal de Nível Superior

FAPERJ
Fundação Carlos Chagas Filho de Amparo à Pesquisa do Estado do Rio de Janeiro

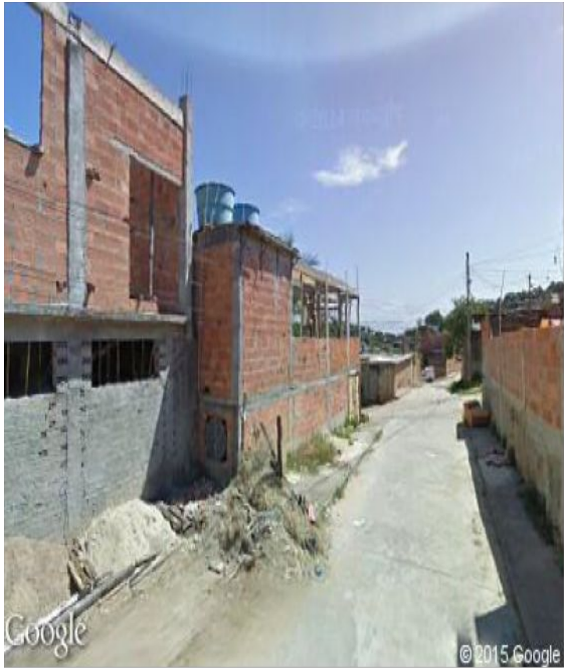
FAPESP
SÃO PAULO RESEARCH FOUNDATION

Agenda

- Context & Motivation
- PlacePulse dataset
- Urban Physical Disorder (UrbanPD) annotations
- Perception model
- Counterfactuals & LLM
- Conclusion

Context & Motivation

Which one seems safer?



Alley street

City Center street

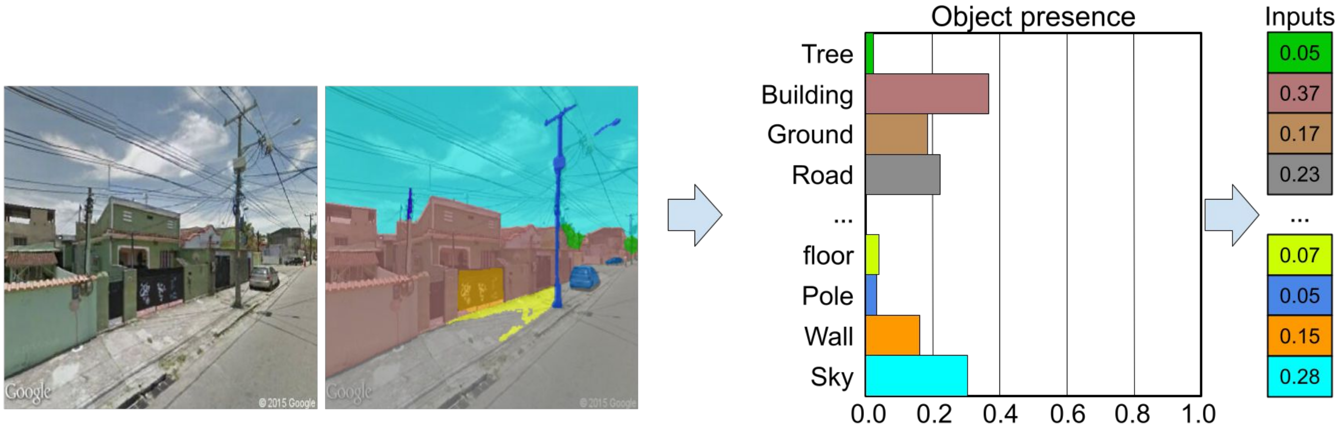
Disorder, social capital, and norm violation

No Littering

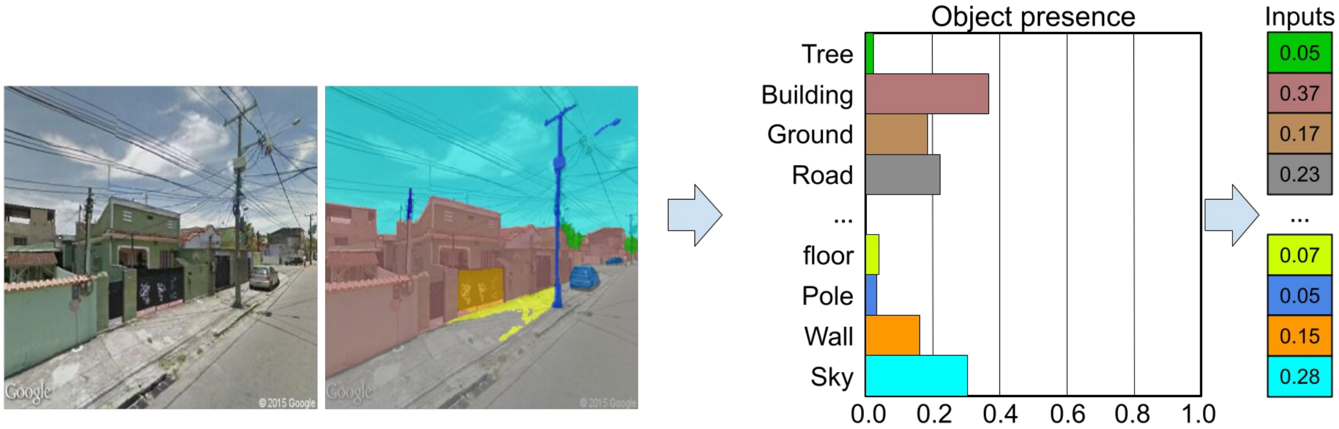
Increase of Littering without Tree presence

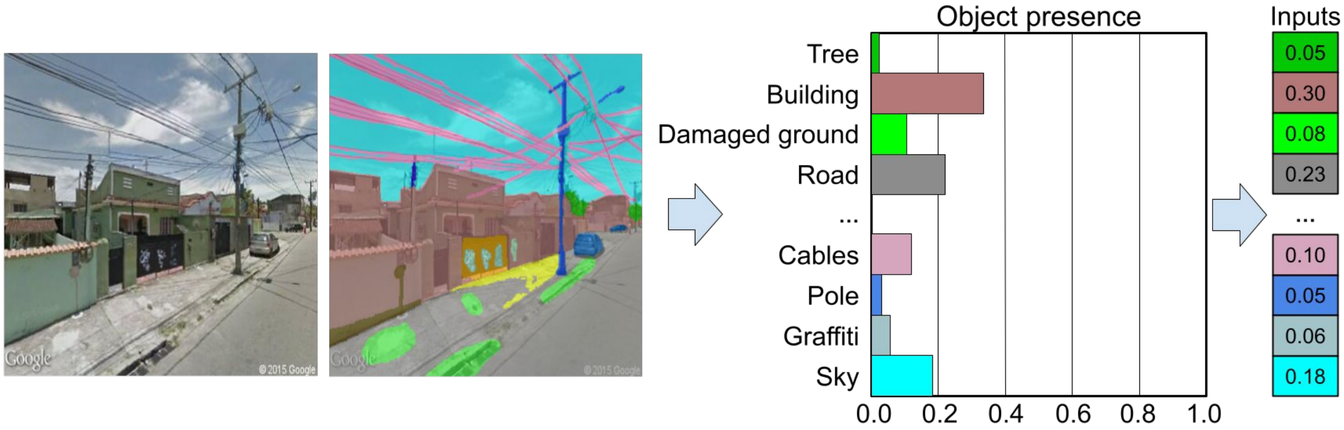
* Disorder, social capital, and norm violation, Keuschnigg et al., 2015

Physical disorder elements



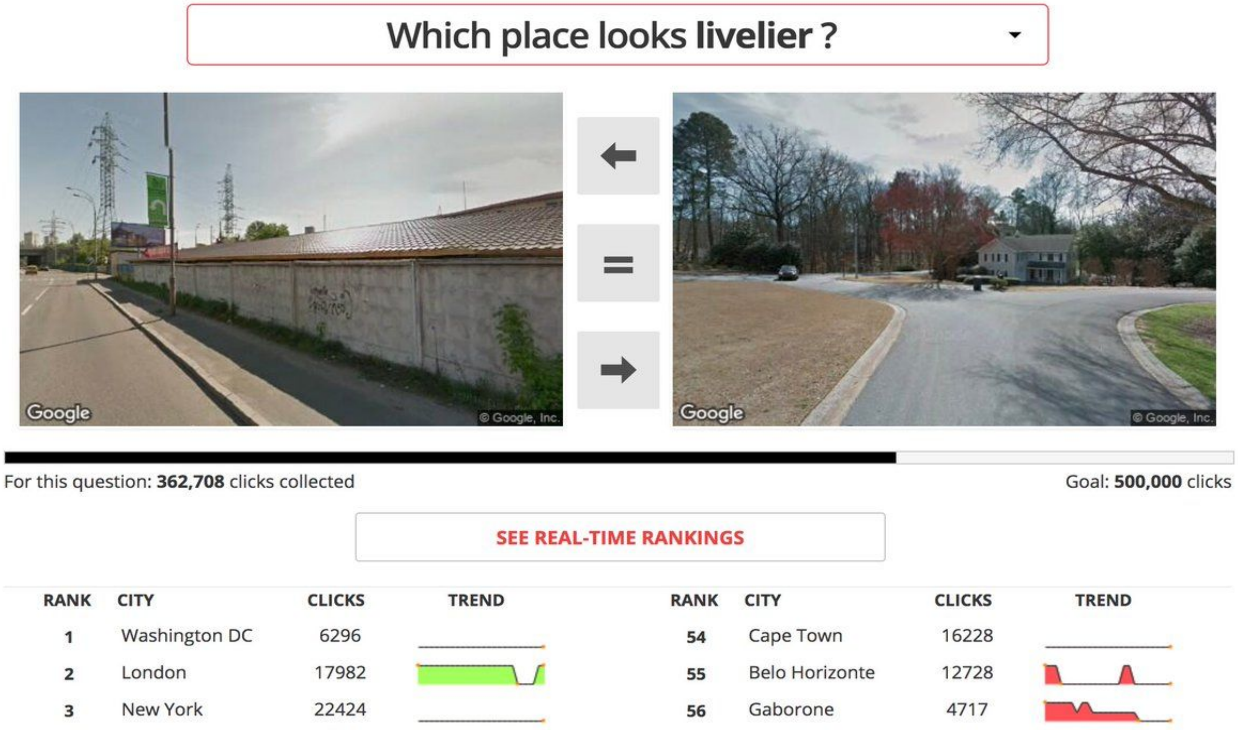
Physical disorder elements





PlacePulse dataset

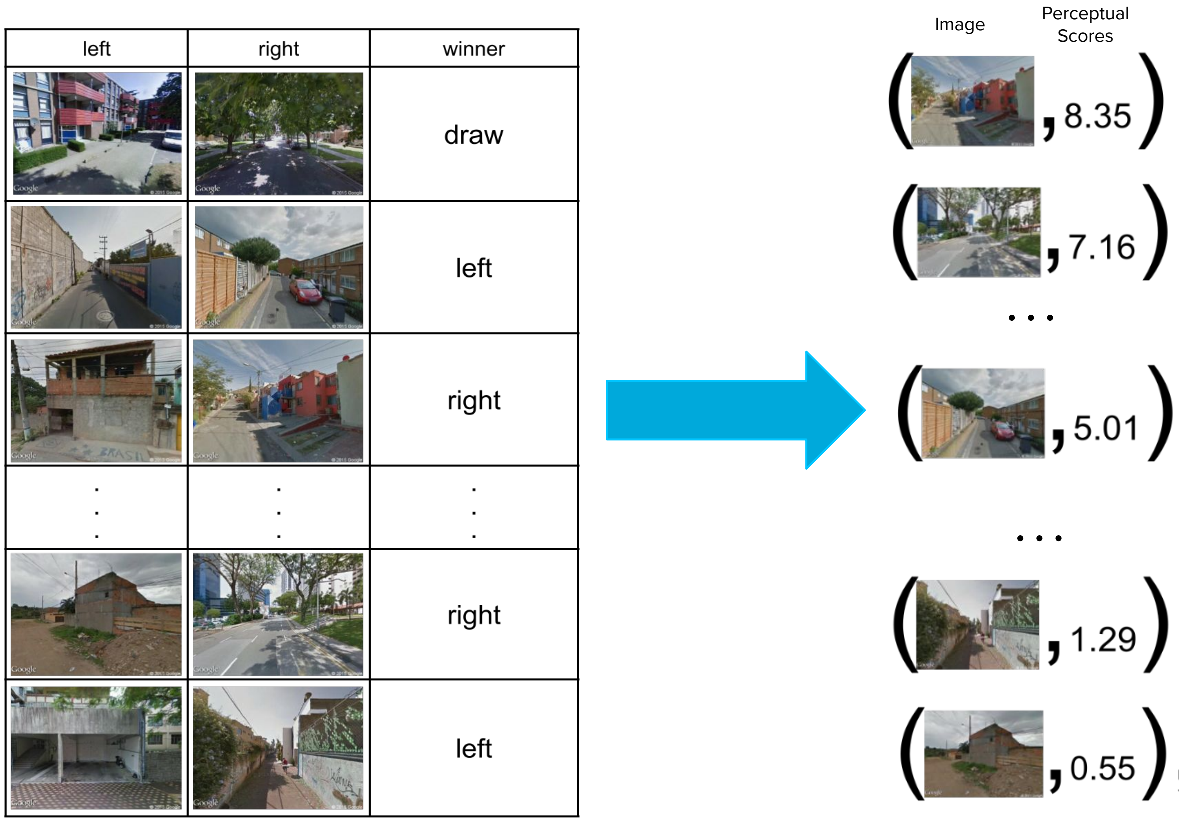
PlacePulse dataset



- 1 223 649 Comparisons
- 111 390 images
- 32 countries
- 56 cities
- 6 categories:
  - Safety
  - Boring
  - Depressing
  - Wealthy
  - Lively
  - Beauty

https://centerforcollectivelearning.org/urbanperception

Strength of schedule



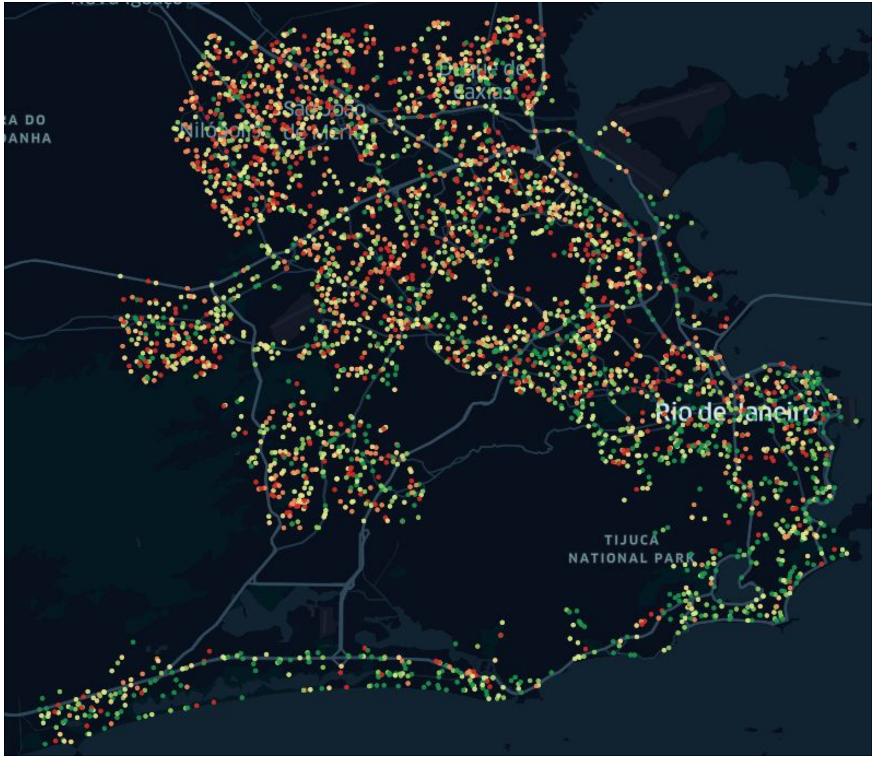
Cities included

Note: Same color means same country.

Cities included

Note: Same color means same country.

Rio de Janeiro samples



Scores from 0 to 10

Low safety scores images

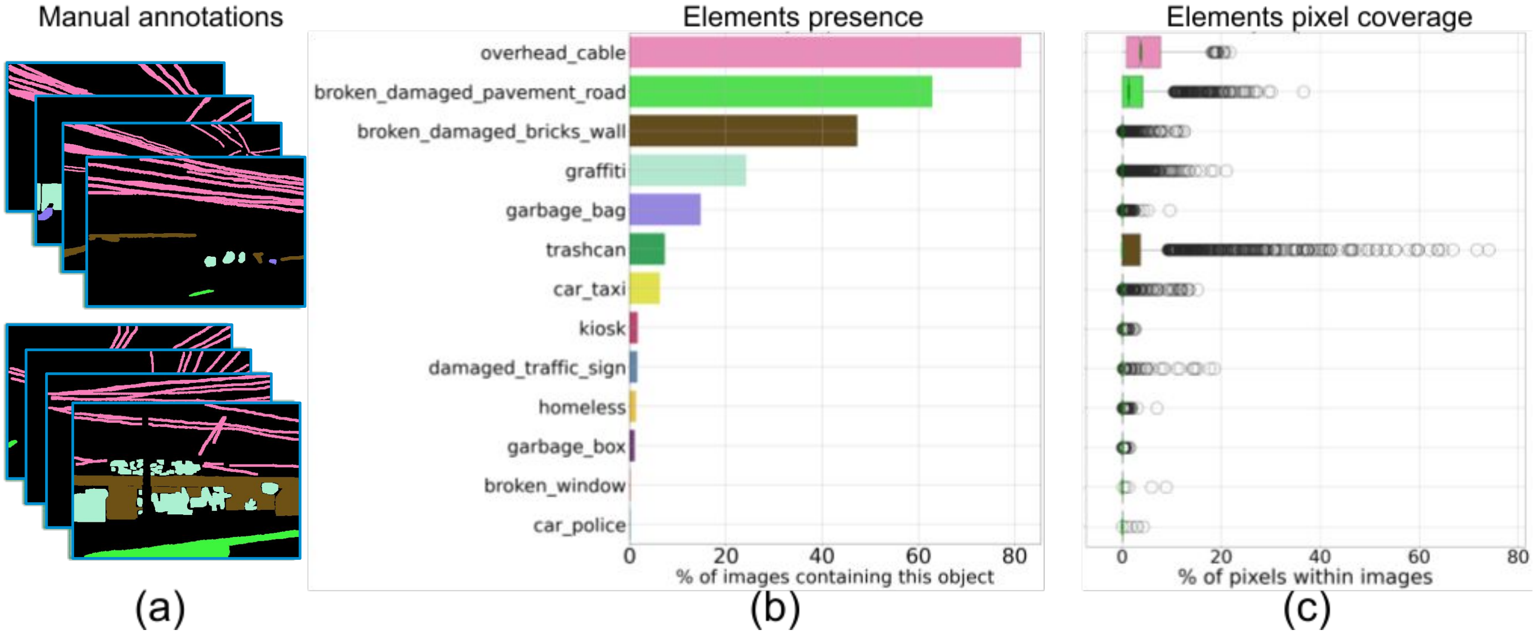
High safety scores images

Urban Physical Disorder

Urban physical disorder annotations

- 3,654 images from the city of Rio de Janeiro were manually segmented
- 13 new classes added (12 if we join garbages)

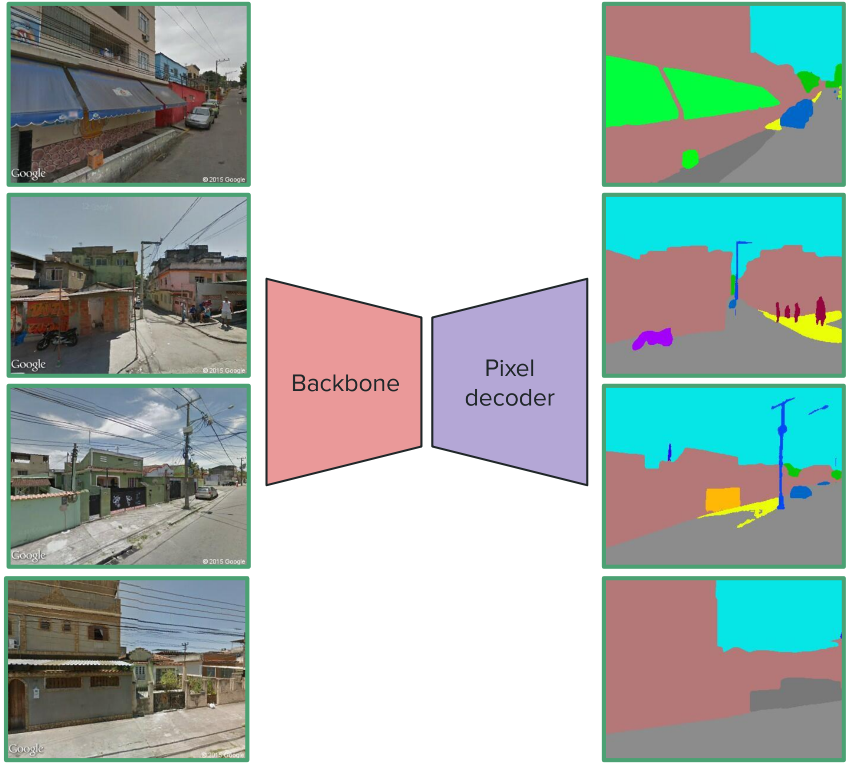
Urban physical disorder annotations



(a) Pixel-level annotation mask samples
(b) Presence of annotated elements
(c) Pixel coverage of elements

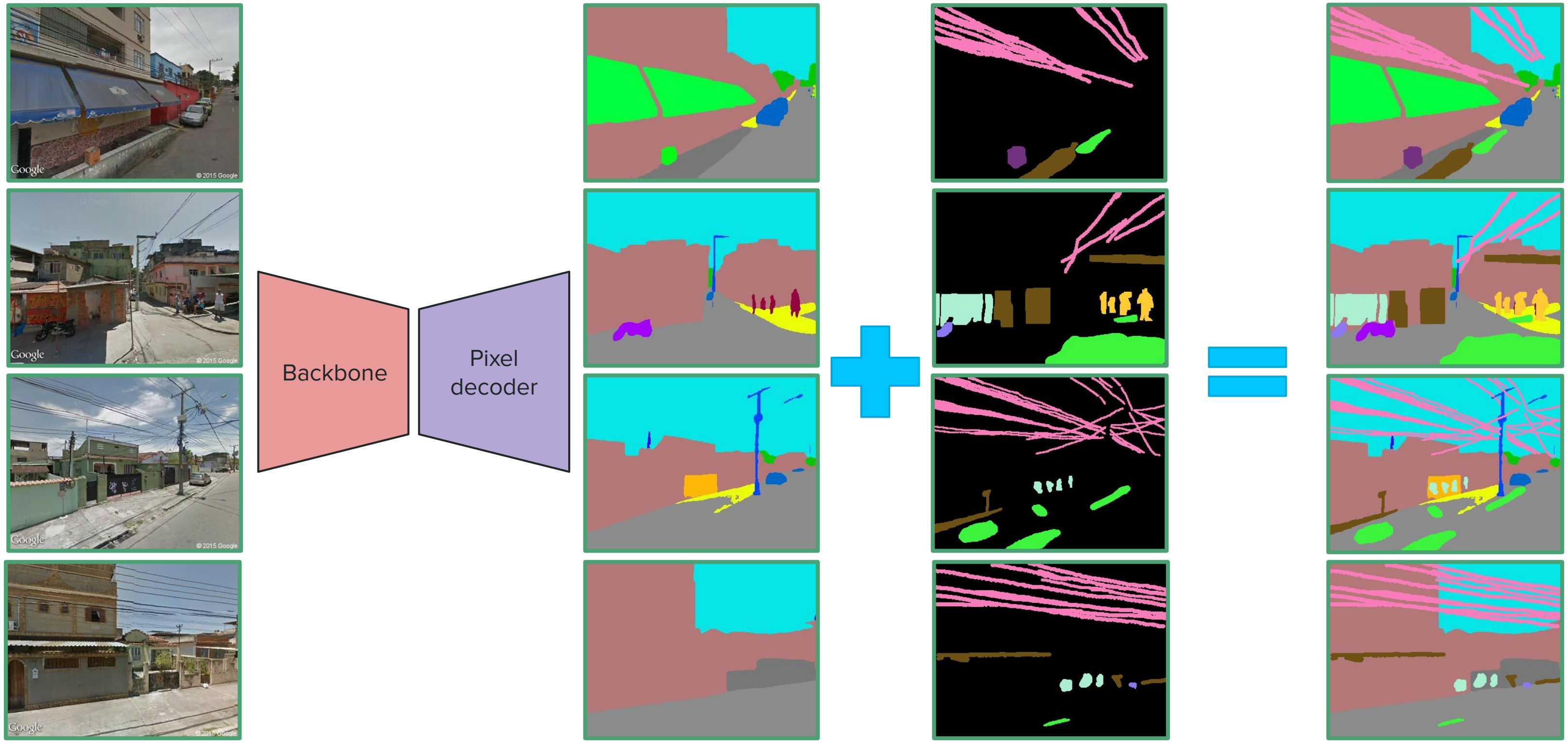
ADE20K

- We use OneFormer pre-trained model



ADE20K

- We use OneFormer pre-trained model

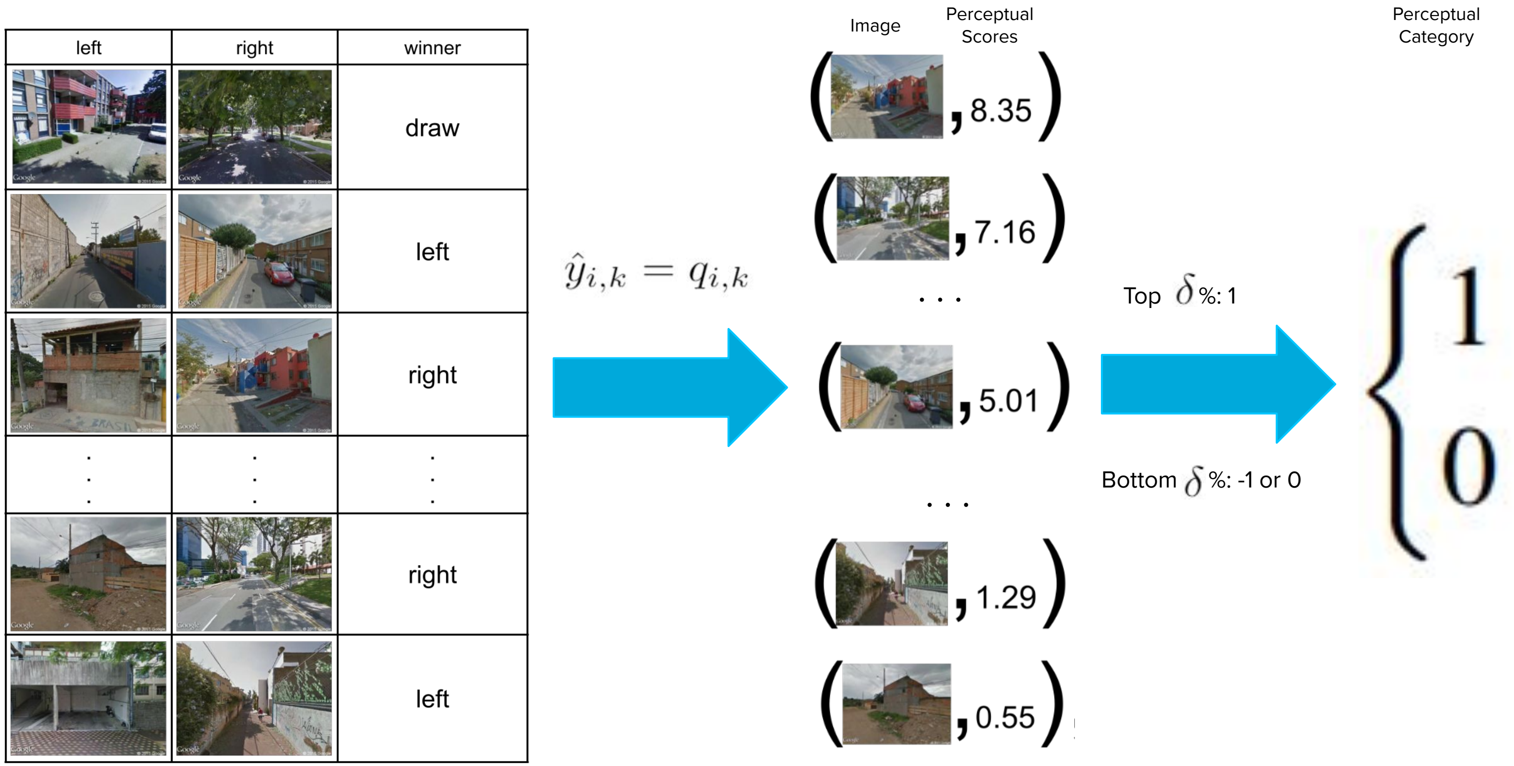


UPD + ADE20K


50f5ebcdfdc9f065f0008589
safety
50f5ec41fdc9f065f00088cb
not safety
50f5ec44fdc9f065f0008900
safety
50f5eaaefdc9f065f0007c15
safety
50f5eb1efdc9f065f0007fdc
not safety
50f5eb27fdc9f065f0008081
safety
50f5ead3fdc9f065f0007d9f
not safety
50f5eb19fdc9f065f0007f7f
safety
50f5ea5efdc9f065f0007ae3
safety
50f5ebcefdc9f065f00085a3
safety
50f5ec36fdc9f065f00087f3
not safety
50f5eb3cfdc9f065f00080bb
not safety
50f5eb24fdc9f065f0008057
not safety
50f5eae9fdc9f065f0007deb
safety
50f5ead6fdc9f065f0007ddb
safety
50f5ec15fdc9f065f00086e2
not safety
50f5ec15fdc9f065f00086e1
not safety
50f5ebc5fdc9f065f00084d4
safety
50f5eab0fdc9f065f0007c3f
safety
50f5ebcffdc9f065f00085b8
safety
50f5eaadfdc9f065f0007c01
safety
50f5ebcefdc9f065f000859b
not safety
50f5ebaffdc9f065f0008499
not safety
50f5eb18fdc9f065f0007f6e
not safety

Perception model

Labeling


left
right
winner
draw
left
right
right
left
$\hat{y}_{i,k} = q_{i,k}$
Image
Perceptual Scores
, 8.35
, 7.16
, 5.01
, 1.29
, 0.55
Top δ%: 1
Bottom δ%: -1 or 0
Perceptual Category
1
0

New groups

Category	# classes	class name
Construction	14	wall, building, ceiling, house fence, column, skyscraper, bridge. bar, shack, tower, stadium fountain, outside door
Floor	7	floor, road, sidewalk ground, sand, path, land
Vegetation	6	tree, grass, plant, field flower, palm
Terrain vehicle	6	car, bus, truck, van motorcycle, bicycle
Body water	5	water, sea, river, waterfall, lake
City elements	4	signboard, streetlight pole, stoplight
Sky	1	sky
Human	1	person
Other	106	not included

New groups

Category	# classes	class name
Construction	14	wall, building, ceiling, house fence, column, skyscraper, bridge. bar, shack, tower, stadium fountain, outside door
Floor	7	floor, road, sidewalk ground, sand, path, land
Vegetation	6	tree, grass, plant, field flower, palm
Terrain vehicle	6	car, bus, truck, van motorcycle, bicycle
Body water	5	water, sea, river, waterfall, lake
City elements	4	signboard, streetlight pole, stoplight
Sky	1	sky
Human	1	person
~~Other~~	~~106~~	~~not included~~

Experiments

We perform two main experiments for ADE20K and our new groups:

- Binary presence/absence: The images are represented by binary visual feature vectors (present (1) or absent (0))
- Pixel ratios: The images are represented as pixel ratio vectors (between 0 and 1)

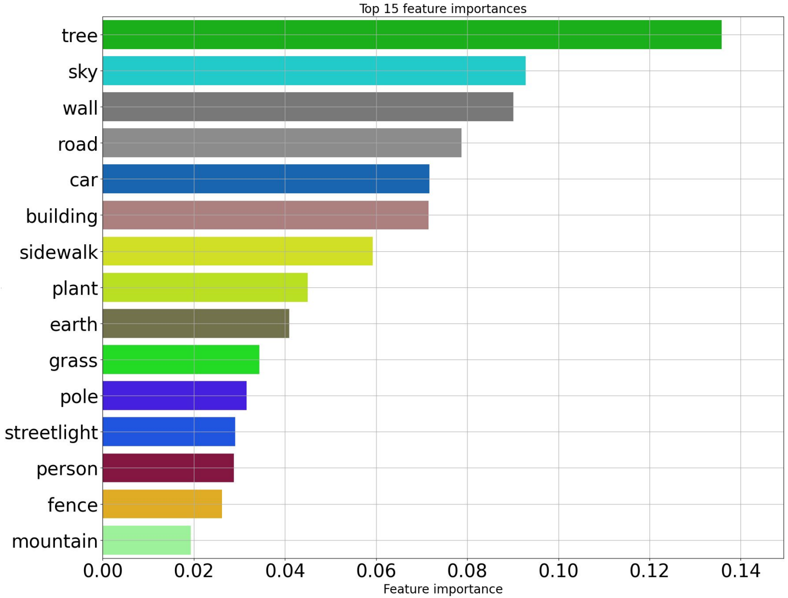
Results

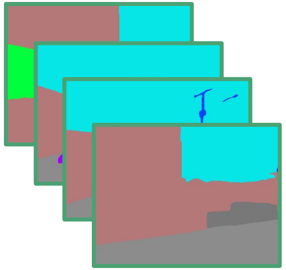
Setting	Categories	Perception	Metrics		
			Precision	Recall	F-1
Binary values	ADE20K (150 classes)	not safe	0.59	0.65	0.62
		safe	0.60	0.55	0.57
	ADE20K+Disorder (163 classes)	not safe	0.64	0.65	0.65
		safe	0.67	0.60	0.63
	Visual elements (8 groups-classes)	not safe	0.52	0.42	0.46
		safe	0.51	0.61	0.55
	Visual elements+Disorder (22 classes)	not safe	0.66	0.71	0.67
		safe	0.65	0.66	0.66

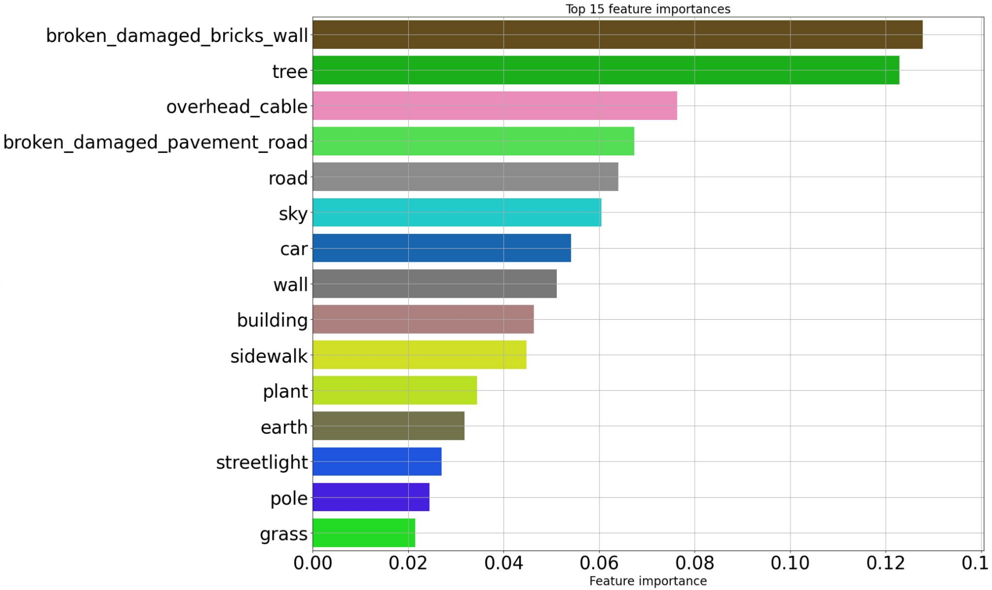
Results

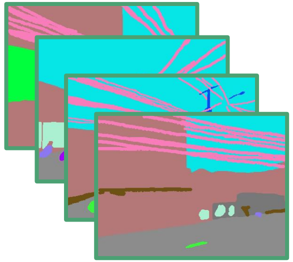
Setting	Categories	Perception	Metrics		
			Precision	Recall	F-1
Pixel ratios	ADE20K (150 classes)	not safe	0.67	0.73	0.69
		safe	0.71	0.63	0.67
	ADE20K+Disorder (163 classes)	not safe	0.70	0.76	0.73
		safe	0.73	0.68	0.70
	Visual elements (8 groups-classes)	not safe	0.69	0.72	0.70
		safe	0.70	0.64	0.66
	Visual elements+Disorder (22 classes)	not safe	0.72	0.77	**0.75**
		safe	0.75	0.69	**0.72**

Feature importance

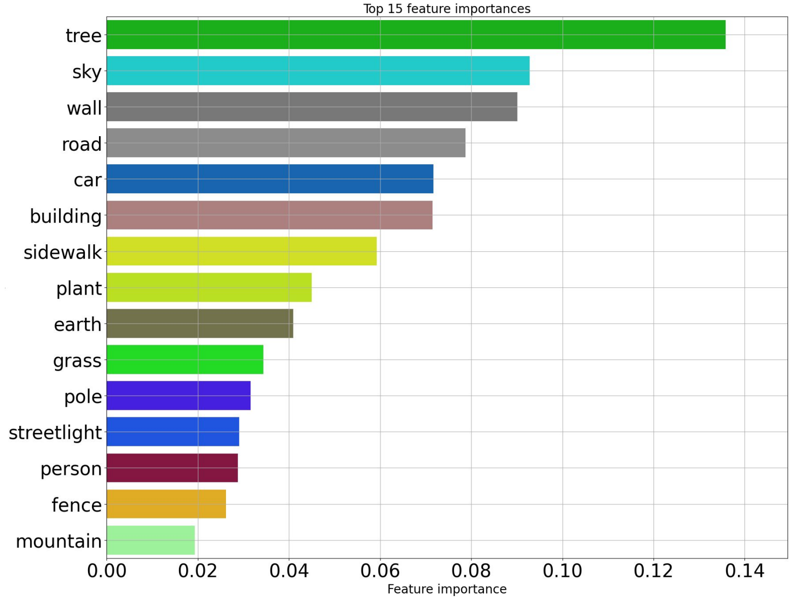


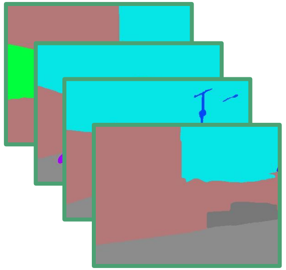


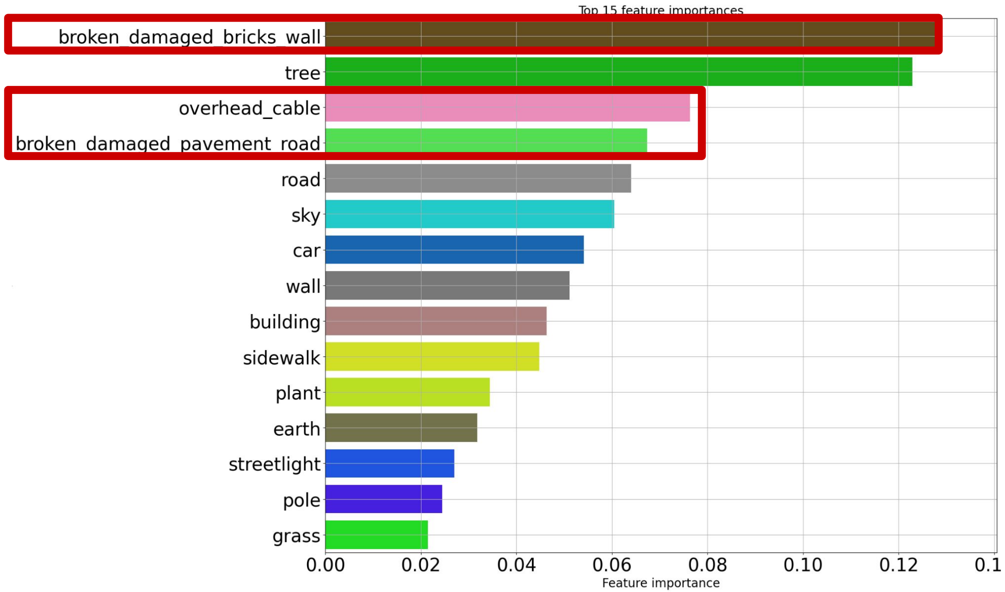


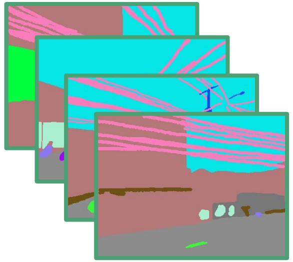


Feature importance



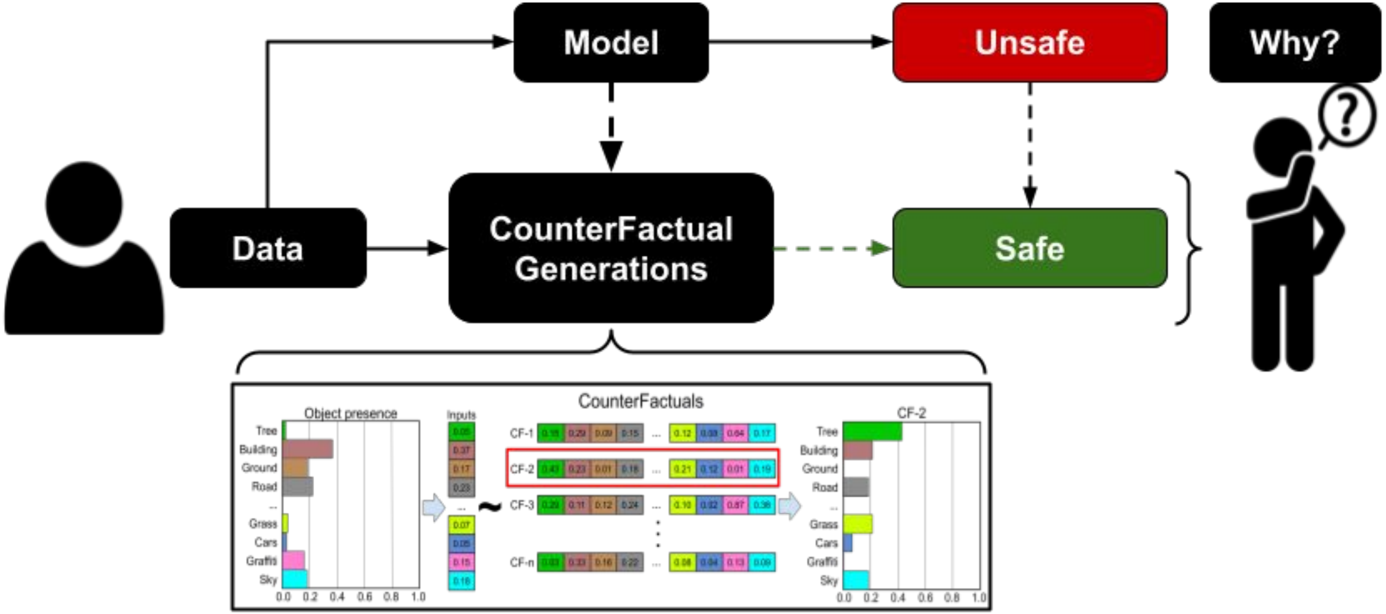






Counterfactuals & LLMs

CounterFactual explanations



CounterFactual

We get counterfactuals for both cases:

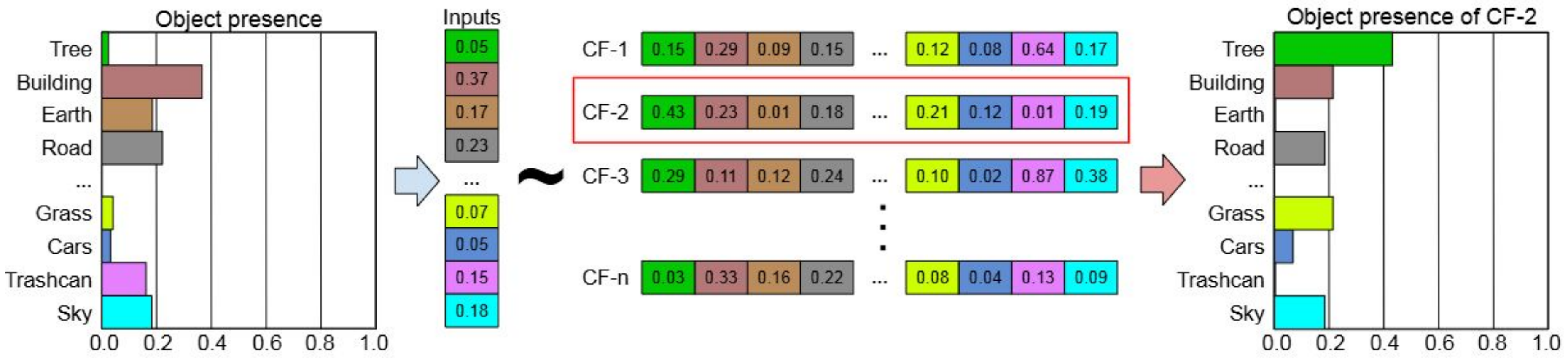
- Binary presence/absence:

$$x' = \arg\min_{x' \in \mathcal{F}} \sum_{i=1}^{n} |x_i - x'_i|$$

- Pixel ratios:

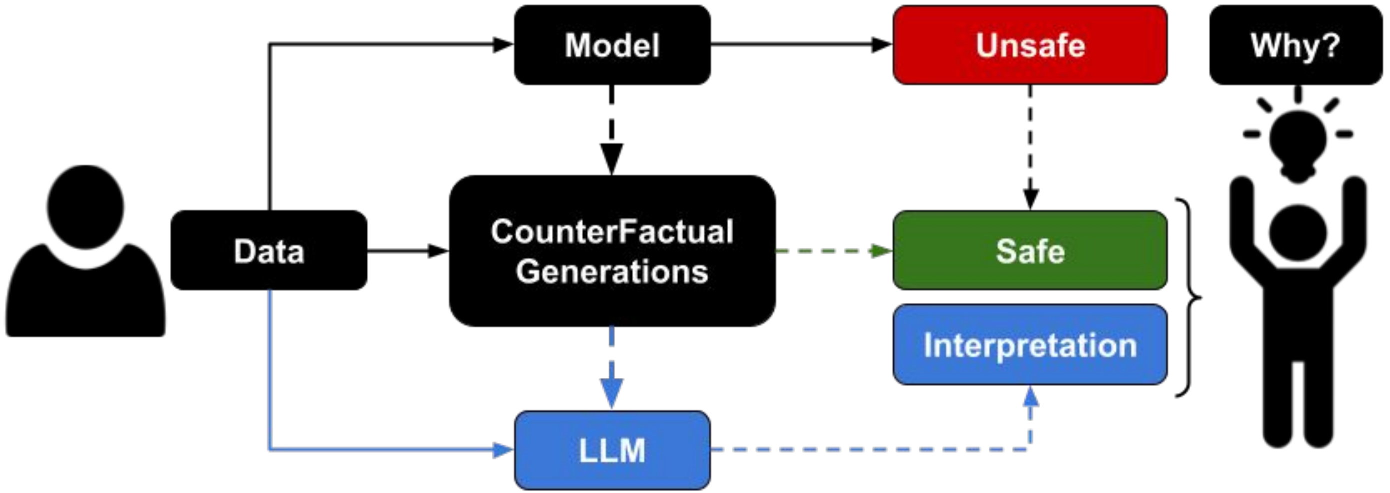
$$x' = \arg\min_{x' \in \mathcal{F}} \mathcal{C}(x, x') + \lambda \cdot \mathcal{L}(f(x'), y')$$

CounterFactual idea



- Dice-ML to generates counterfactuals
- Identify what objects should be removed or increased

LLM interpretations



LLM interpretations

Image			
Δ safety probability	0.45	0.25	0.04
Objects Removed	graffiti, garbage, damaged sidewalk	overhead cables, damaged road	garbage bags
Objects Added	trees, walls, fences	Trees, grass	tree, grass, road
LLM interpretation	It's better to remove graffiti from walls, repair brick walls, and avoid overhead cables	The overhead cables should be removed, and adding grass and trees along the road will help increase people's sense of safety.	This street is already in good condition, but by incorporating more greenery and eliminating garbage bags, it could be improved even further.

Conclusion

Conclusion

- **UrbanPhysicalDisorder annotations**: 13 urban physical-disorder elements were annotated across 3,654 images from Rio de Janeiro.

- **Counterfactuals** demonstrate the relevance of including physical-disorder elements by showing how increasing or decreasing their presence affects the outcome.

- **LLMs** successfully translate non–human-readable vectors into natural language, improving the understanding of which elements should be modified.

THANKS!

IEEE BIG DATA 2025

UrbanPhysicalDisorder-4K

Understanding Urban Perception **via Counterfactuals** and Street View Signs of **Physical Disorder**

Felipe Moreno-Vera

Andres De-la-Puente

Jorge Poco

Fundação Getulio Vargas / Visual Data Science Lab

www.visualdslab.com

FGV EMAp V-DS FAPERJ Fundação Carlos Chagas Filho de Amparo à Pesquisa do Estado do Rio de Janeiro FAPESP SÃO PAULO RESEARCH FOUNDATION