FGV EMAp

IEEE BIG DATA 2025

UrbanPhysicalDisorder-4K

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

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

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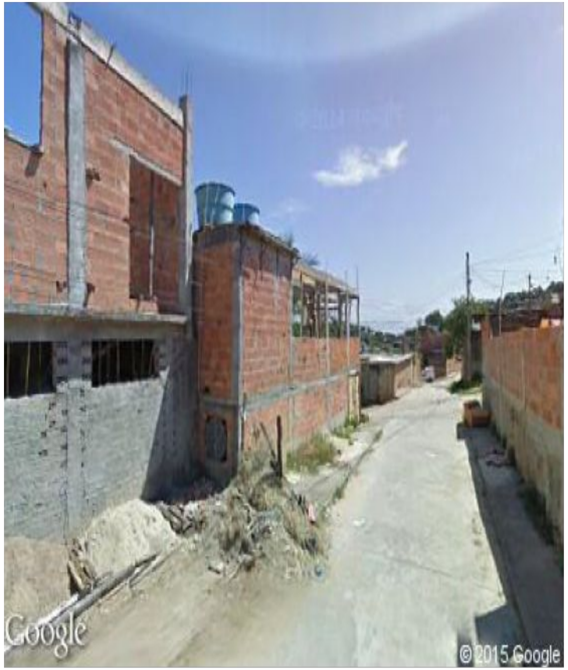
Agenda

- 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

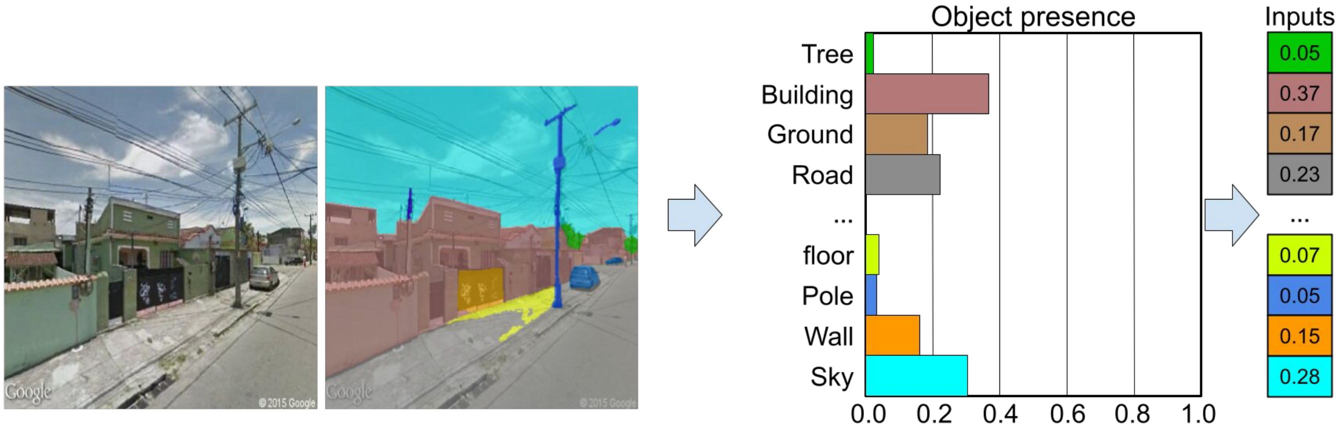
Disorder, social capital, and norm violation

No Littering

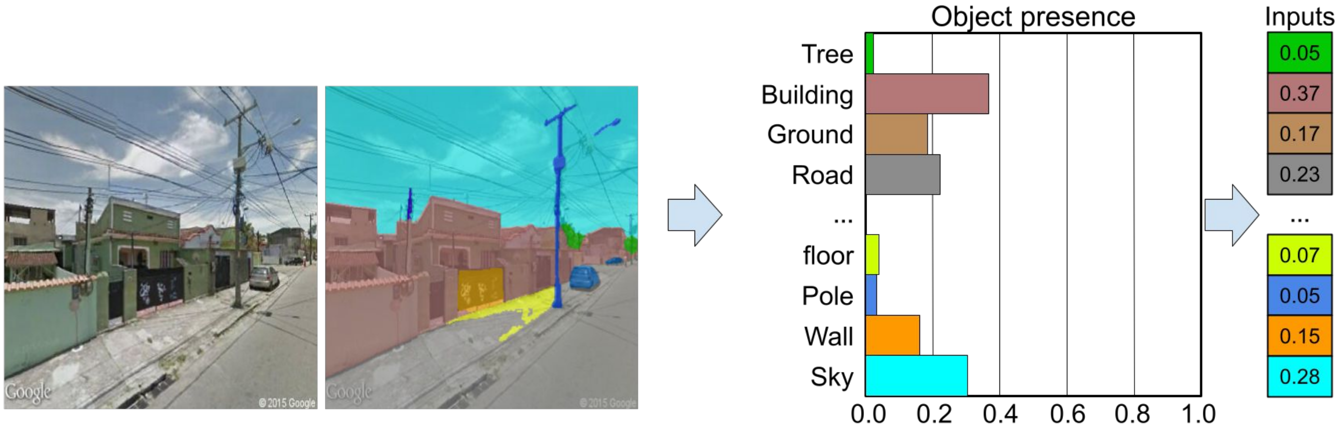
Increase of Littering without Tree presence

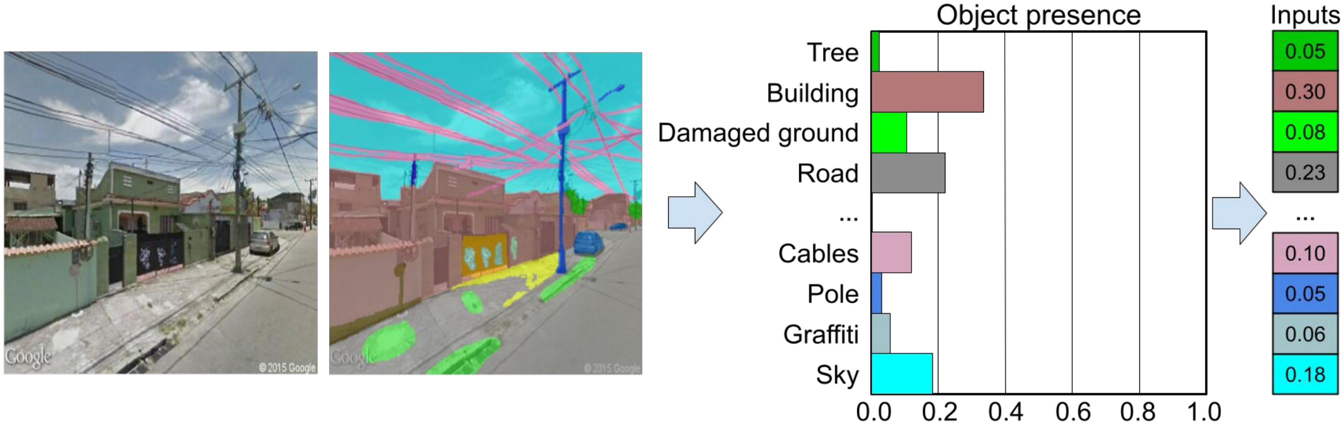
* Disorder, social capital, and norm violation, Keuschnigg et al., 2015

Urban elements segmentation



Physical disorder elements



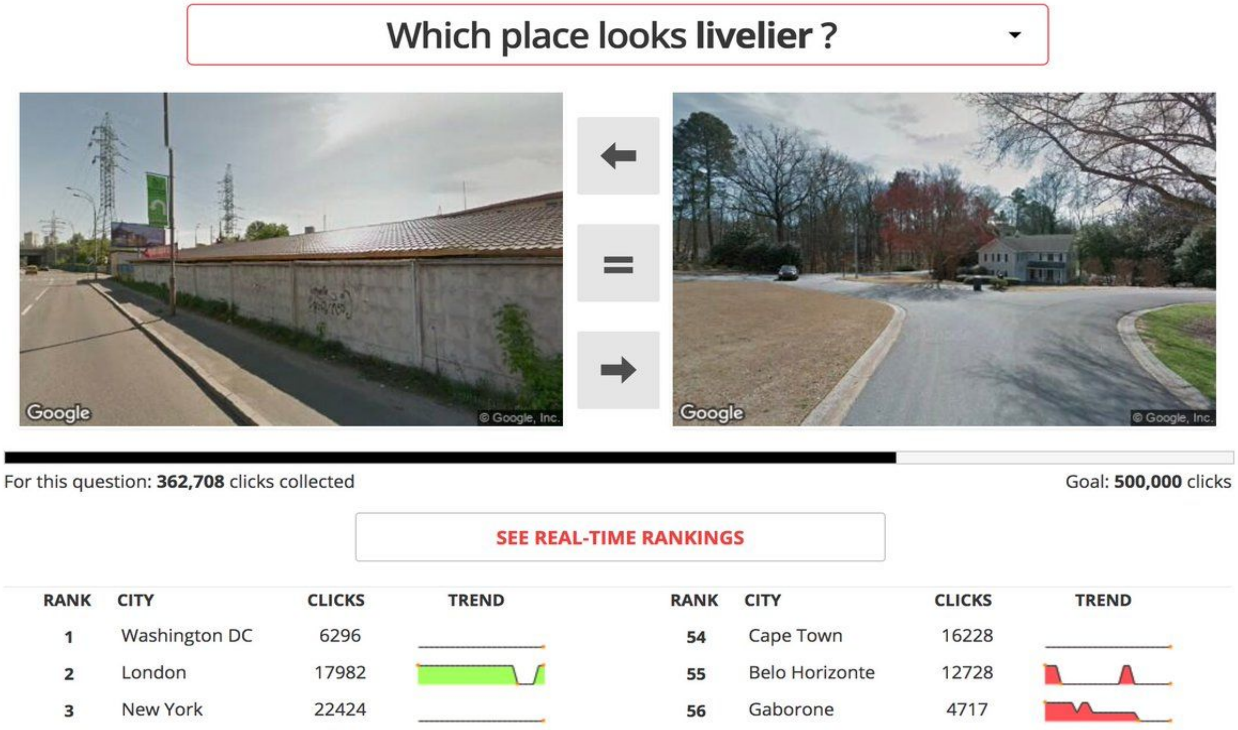


Contributions

- UrbanPhysicalDisorder dataset
- Analysis of the Physical disorder relevance
- LLMs-based method to interpret counterfactuals

PlacePulse dataset

PlacePulse dataset

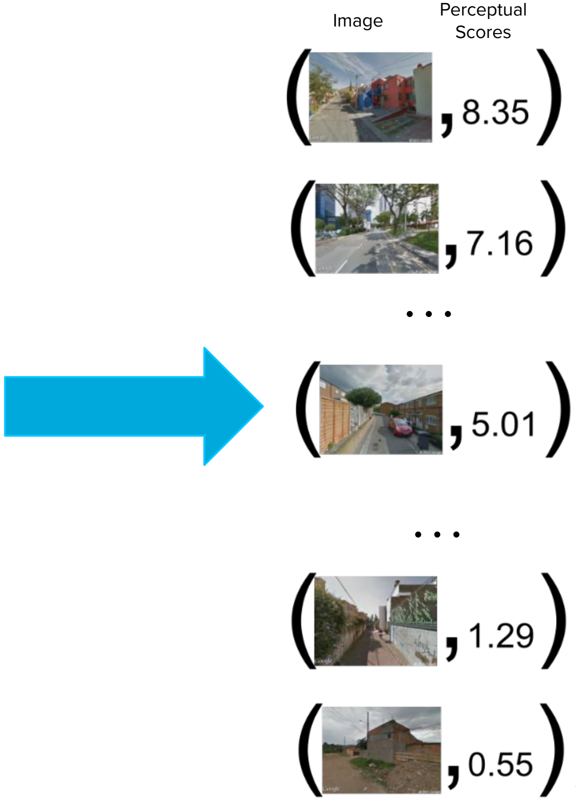


- 1 223 649 Comparisons
- 111 390 images
- 32 countries
- 56 cities
- 6 categories:
  - Safety
  - Boring
  - Depressing
  - Wealthy
  - Lively
  - Beauty

https://centerforcollectivelearning.org/urbanperception

Strength of schedule

left	right	winner
		draw
		left
		right
⋮	⋮	⋮
		right
		left



Cities included

Note: Same color means same country.

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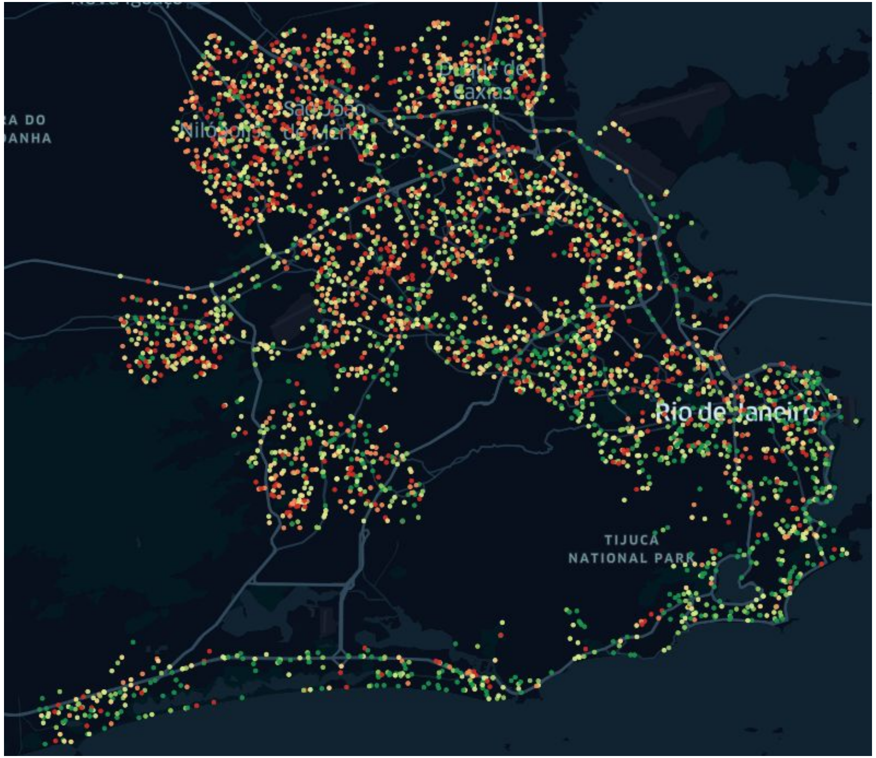
Rio de Janeiro samples



Scores from 0 to 10

Low safety scores images

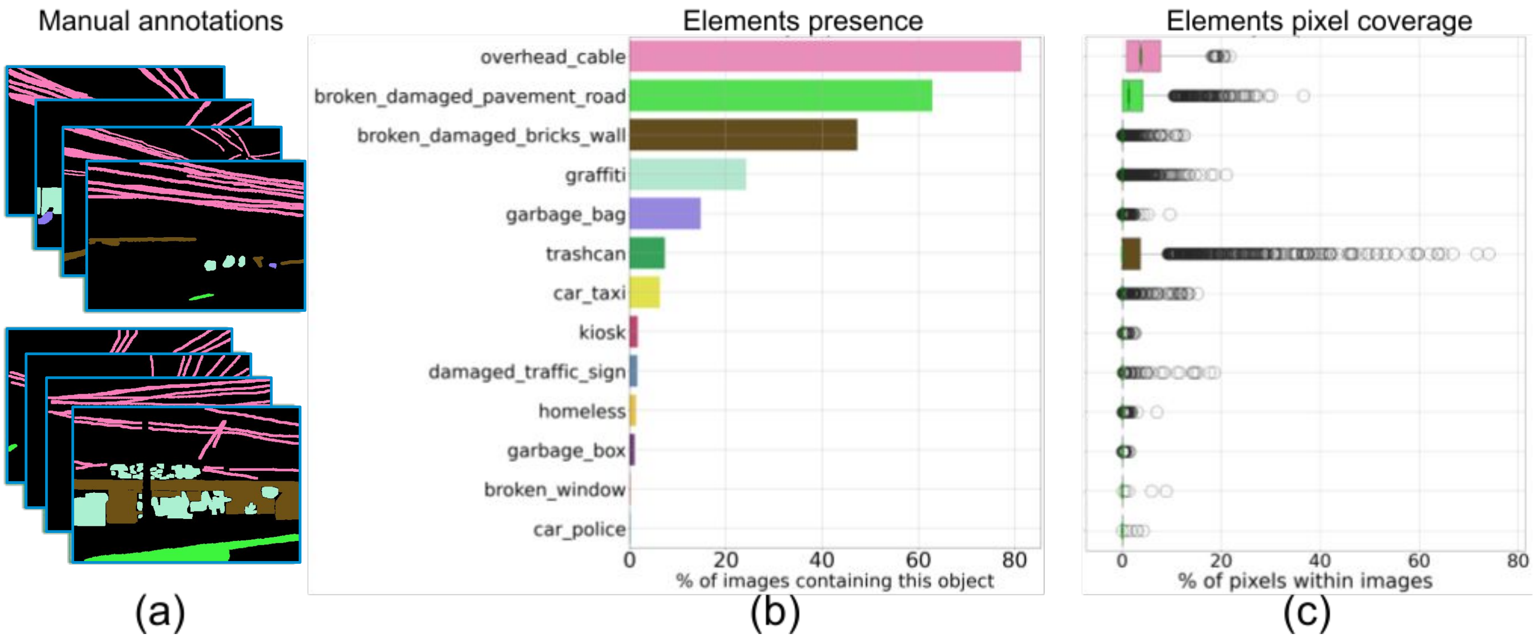
High safety scores images

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)

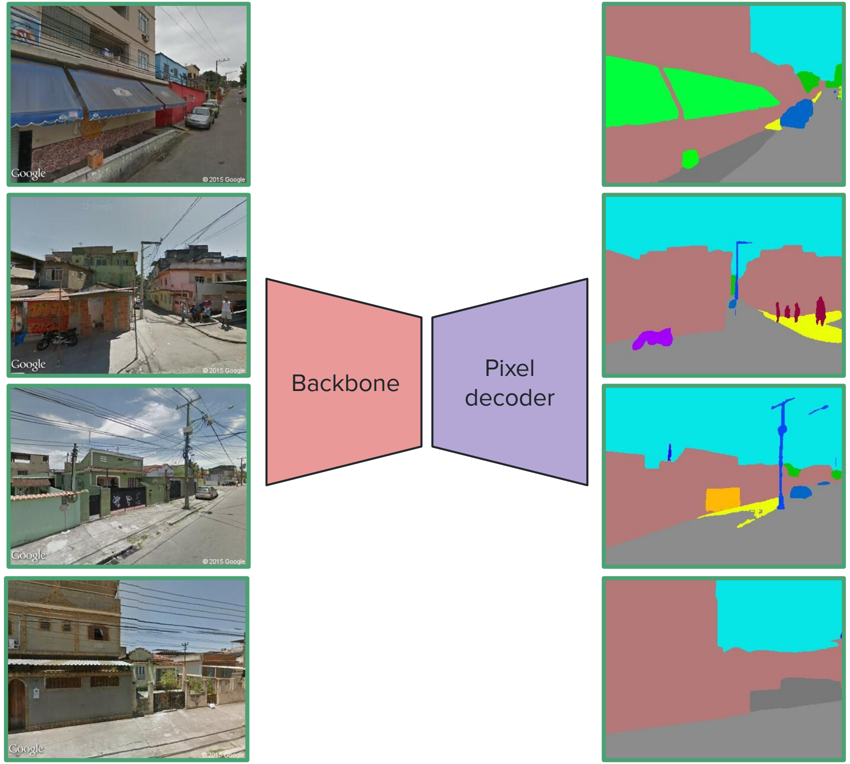
Urban physical disorder annotations



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

ADE20K

- We use OneFormer pre-trained model



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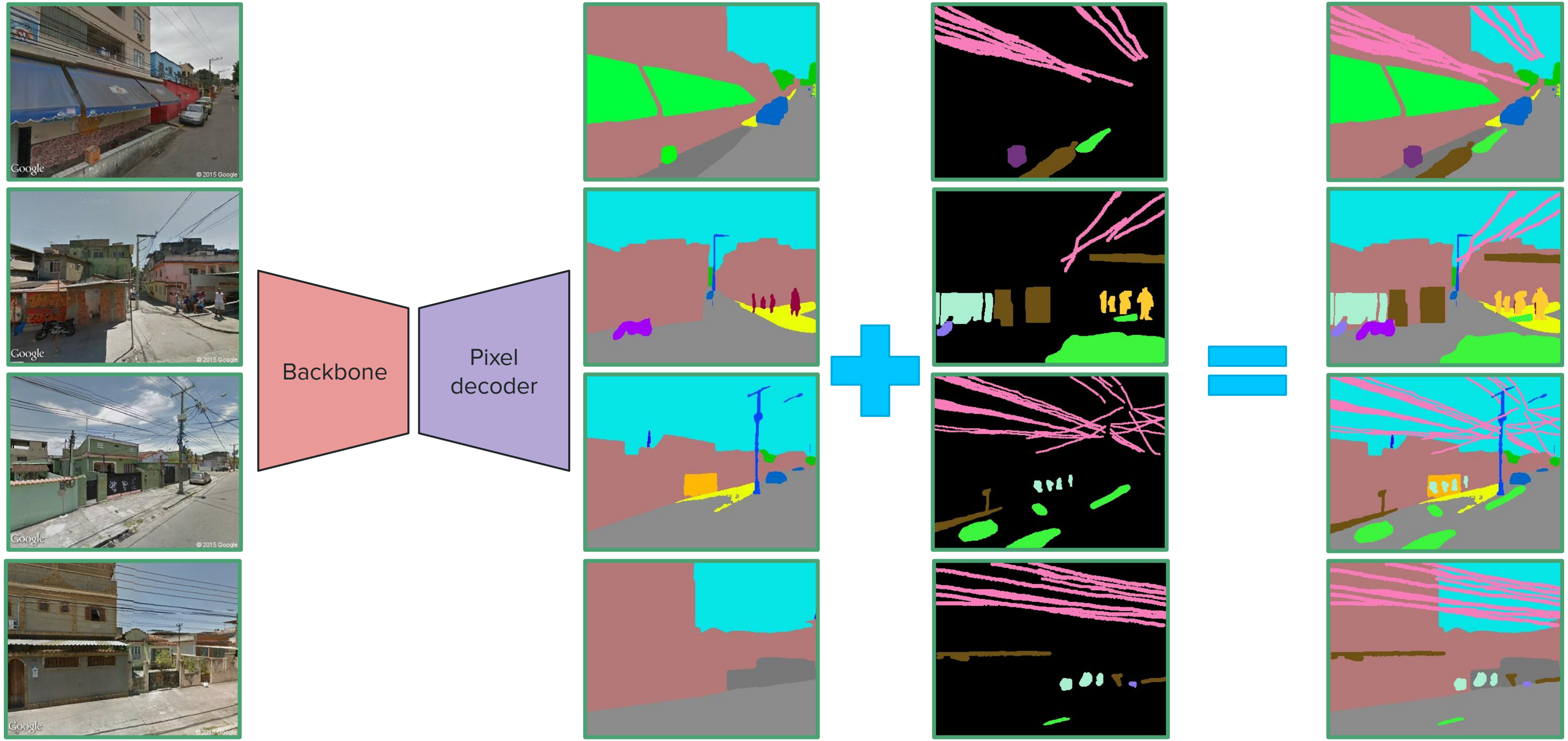

UPD + ADE20K

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
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safety
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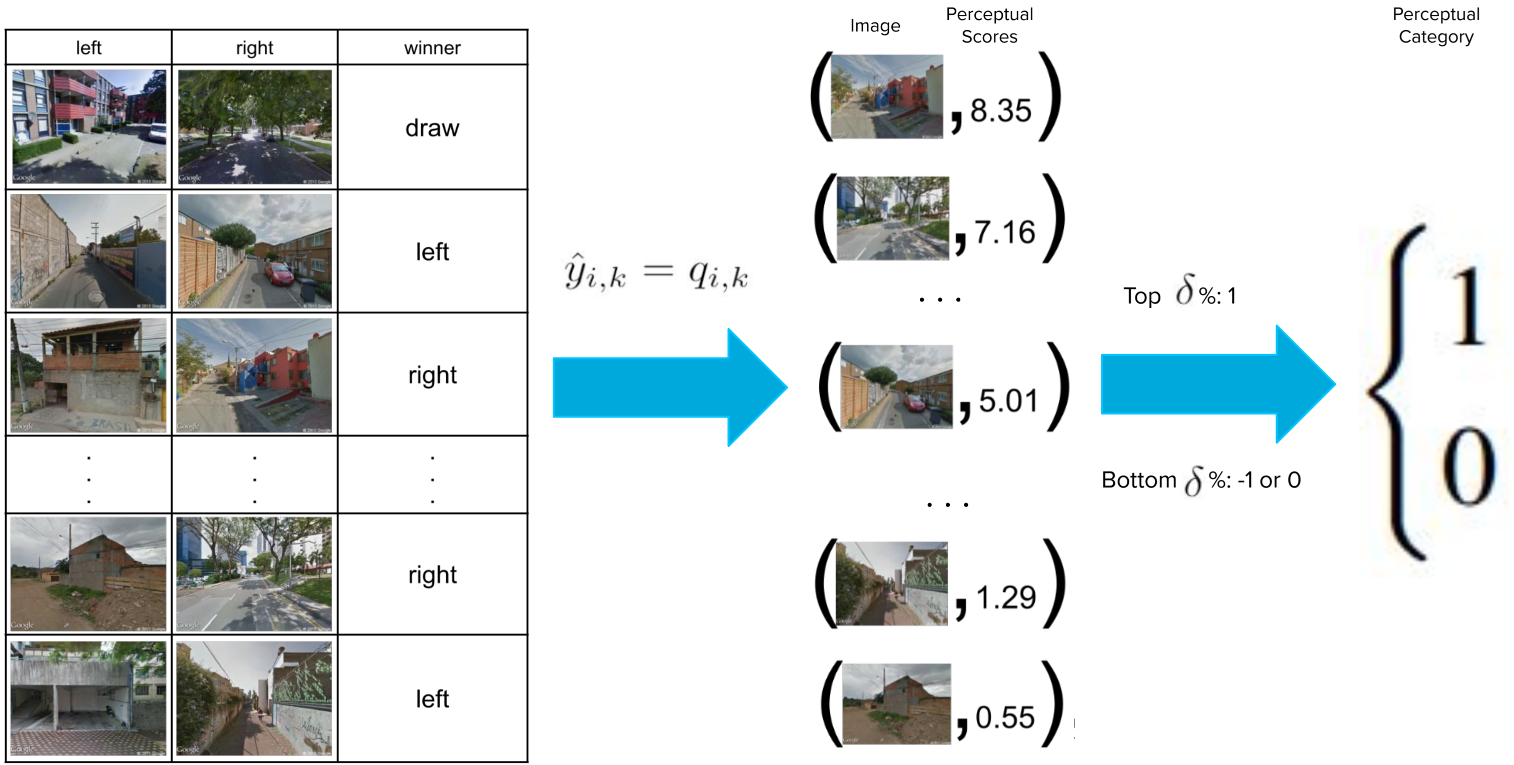
safety
50f5ebcffdc9f065f00085b8
safety
50f5eaadfdc9f065f0007c01
safety
50f5ebcefdc9f065f000859b
not safety
50f5ebaffdc9f065f0008499
not safety
50f5eb18fdc9f065f0007f6e
not safety

Experiments

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

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~~Other~~	~~106~~	~~not included~~

New groups + physical disorders

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
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UrbanPD-4k

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21 classes!!!

Experiments

We perform two main experiments for ADE20K and UrbanPD-4k (visual elements + disorder):

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- Binary presence/absence: The images are represented by binary visual feature vectors (present (1) or absent (0))

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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

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We perform two main experiments for ADE20K and UrbanPD-4k (visual elements + disorder):

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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**

Counterfactuals & LLMs

CounterFactuals

We analyze the best case

Setting	Categories	Perception	Metrics		
			Precision	Recall	F-1
	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
Pixel ratios	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**

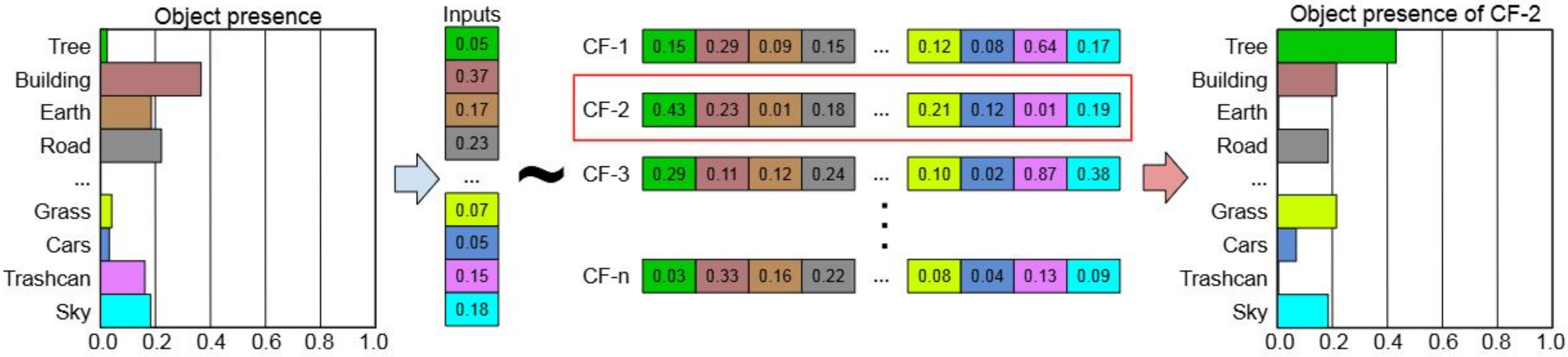
Counterfactuals

Counterfactuals

- We apply 100 counterfactuals to study the relevance of each visual element (object and disorder)

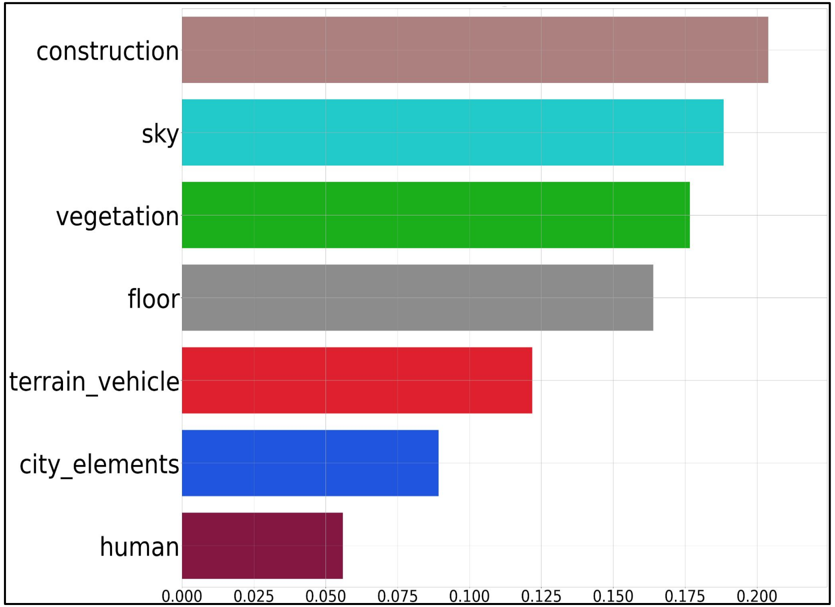
- We define a Δ safety probability to measure the difference of probability to an image be classified as safe (from unsafe).

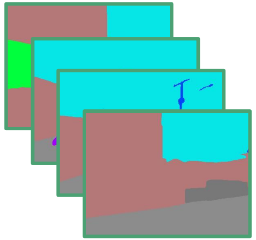
Counterfactuals



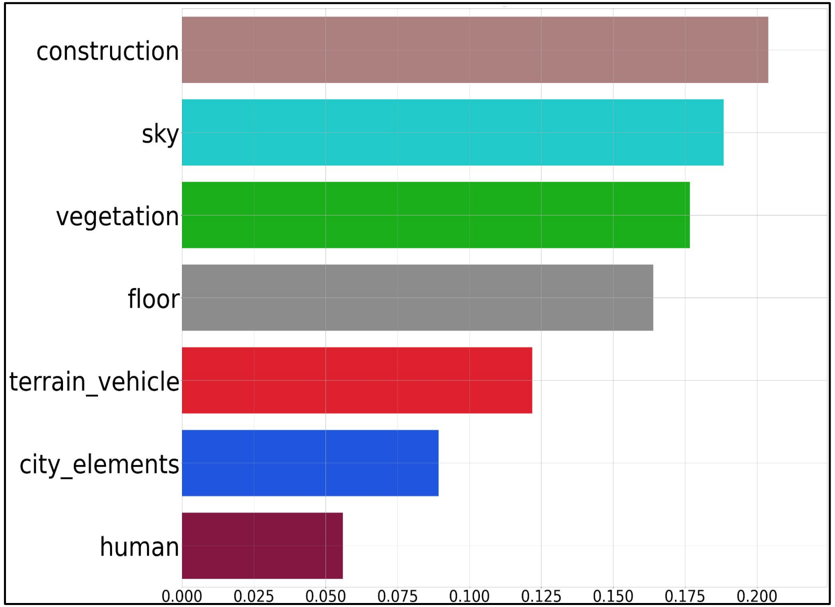
- Dice-ML to generates counterfactuals
- Identify what objects should be removed or increased

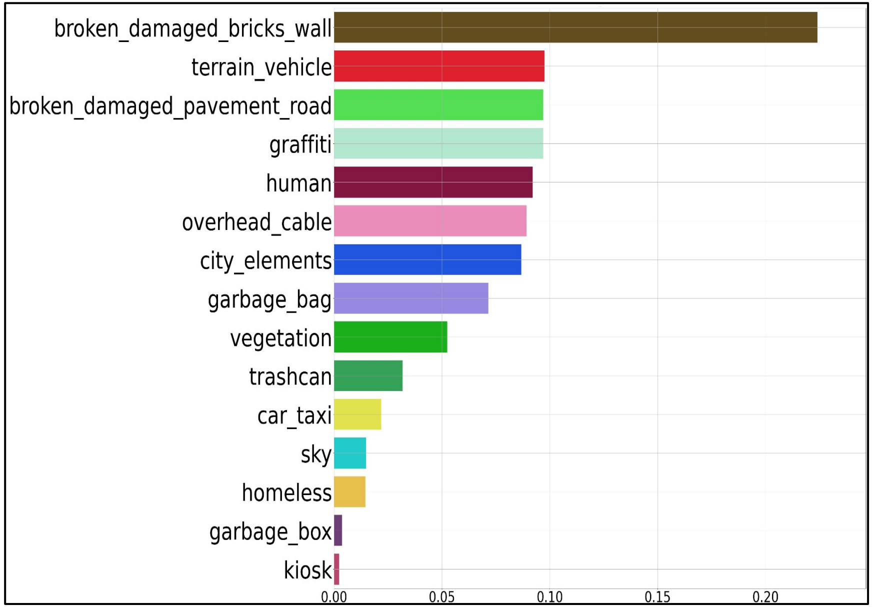
Counterfactuals

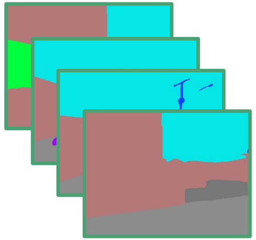


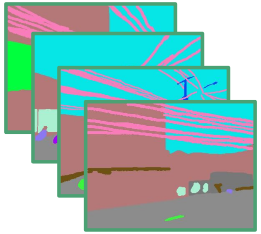


Counterfactuals

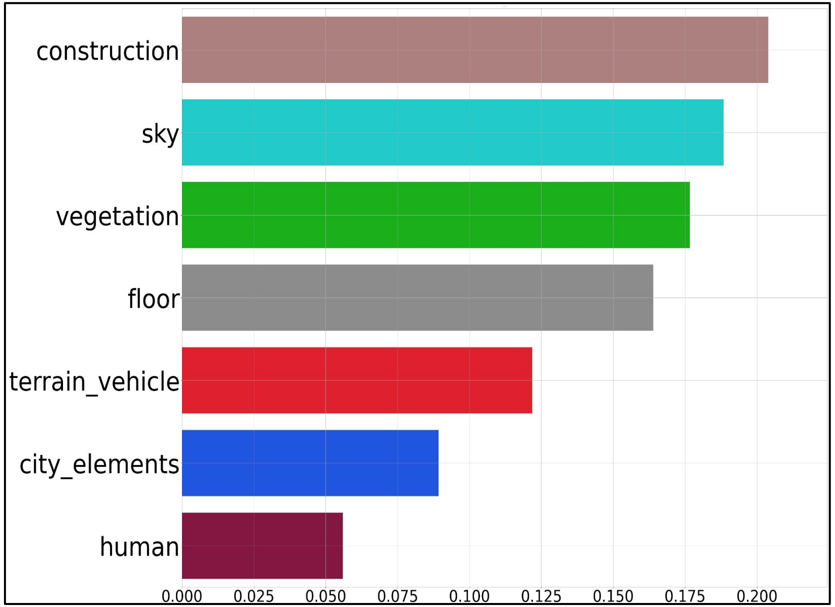


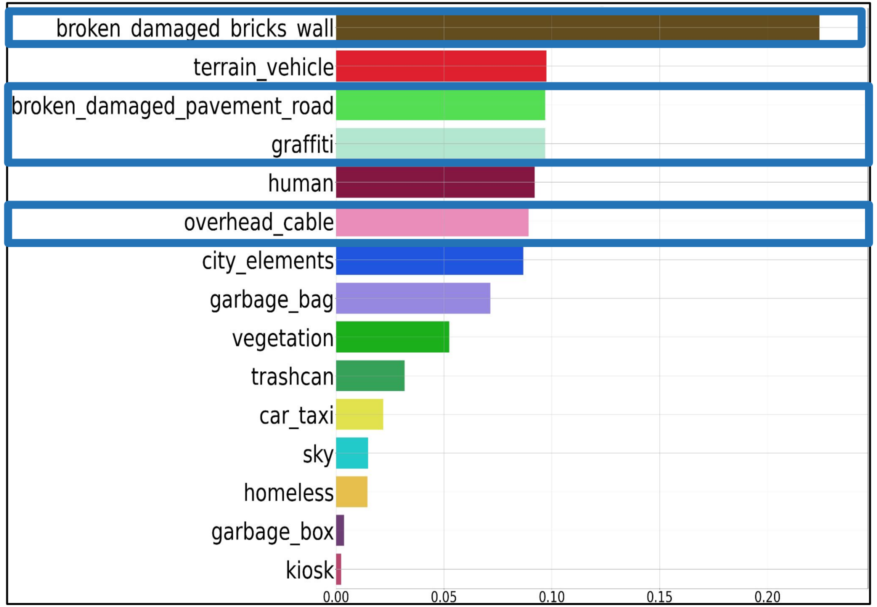


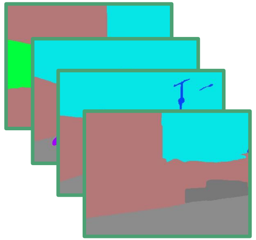


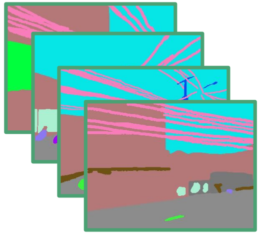


Counterfactuals: Most relevant objects changed

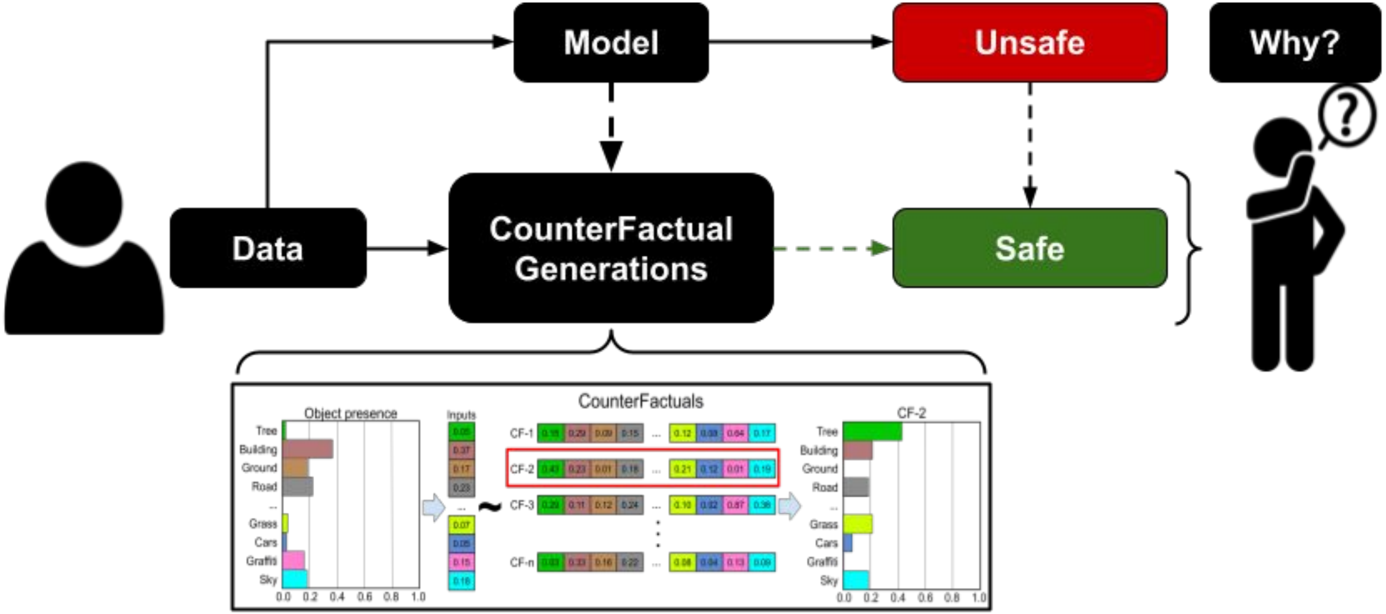




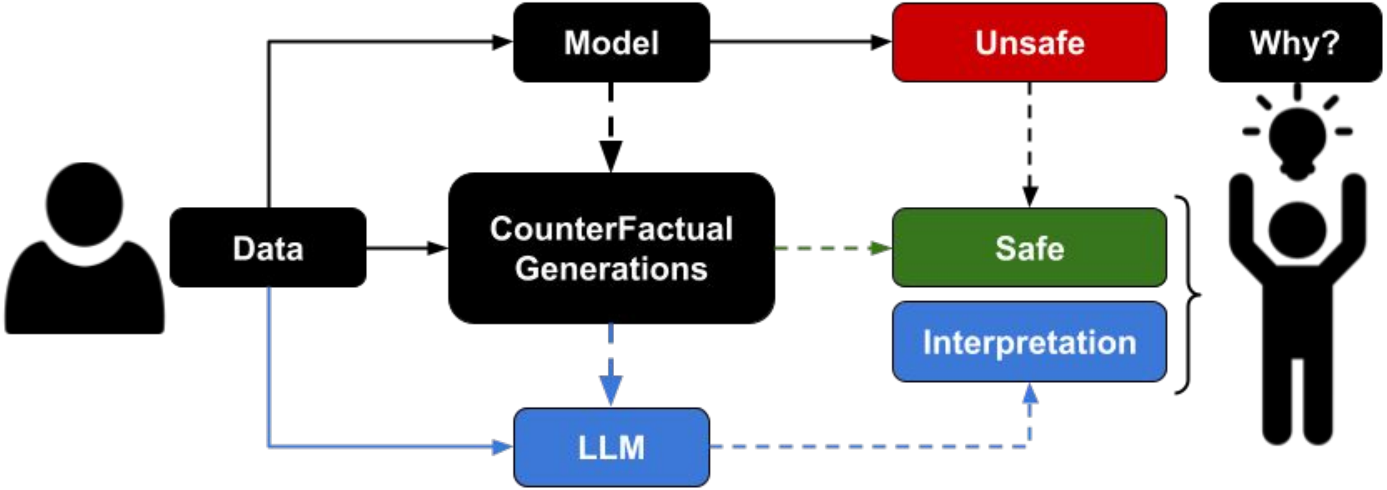




CounterFactual explanations



LLM interpretations



LLM interpretations: unsafe sample

Image	
Δ safety probability	0.45
Objects Removed	graffiti, garbage, damaged sidewalk
Objects Added	trees, walls, fences
LLM interpretation	It's better to remove graffiti from walls, repair brick walls, and avoid overhead cables

LLM interpretations: neutral/borderline sample

Image	
Δ safety probability	0.25
Objects Removed	overhead cables, damaged road
Objects Added	Trees, grass
LLM interpretation	The overhead cables should be removed, and adding grass and trees along the road will help increase people's sense of safety.

LLM interpretations: safe sample

Image	
Δ safety probability	0.04
Objects Removed	garbage bags
Objects Added	tree, grass, road
LLM interpretation	This street is already in good condition, but by incorporating more greenery and eliminating garbage bags, it could be improved even further.

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

Conclusions

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

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

- **LLMs-based method to interpret counterfactuals:** translate translate non–human-readable vectors into natural language can improve the understanding of which elements should be modified.

THANKS!

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