

# UrbanPhysicalDisorder-4K

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

**Felipe Moreno-Vera**



Andres De-la-Puente



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Fundação Getulio Vargas / Visual Data Science Lab  
[www.visualdslab.com](http://www.visualdslab.com)

# Agenda

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

# **Context & Motivation**

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# Which one seems safer?



Alley street



City Center street

# Disorder, social capital, and norm violation

No Littering

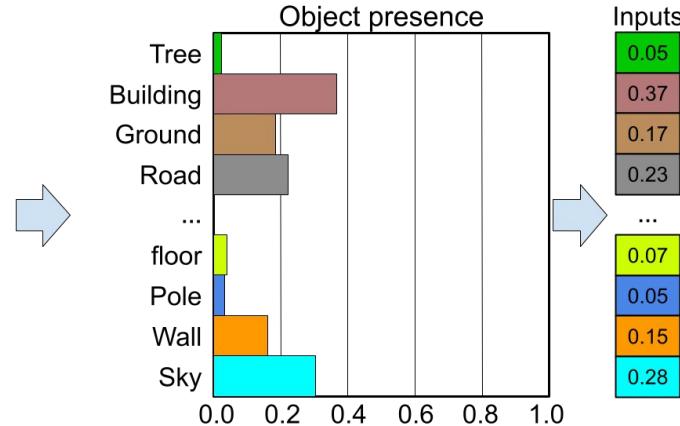


Increase of Littering without Tree presence

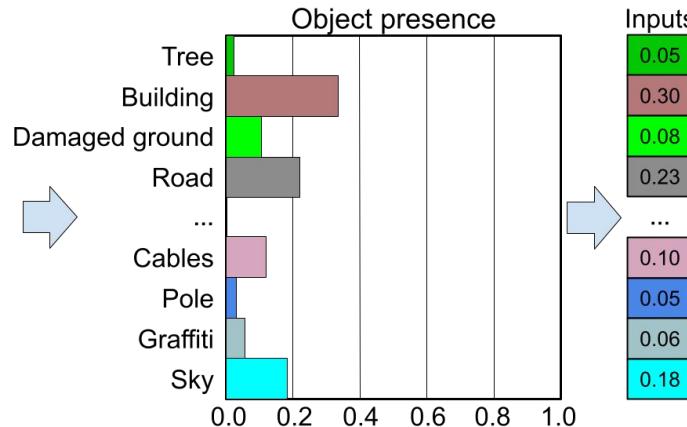
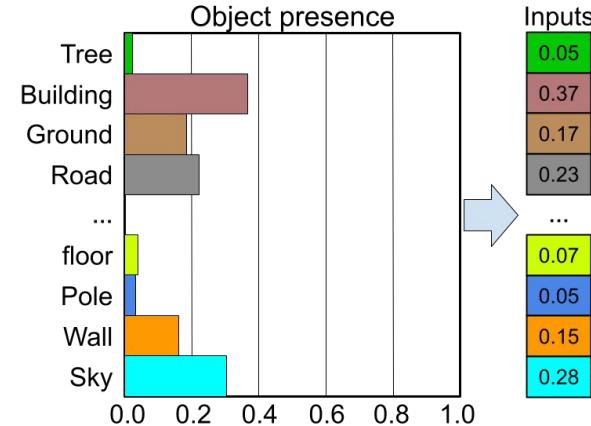


\* [Disorder, social capital, and norm violation](#), Keuschnigg et al., 2015

# Physical disorder elements



# Physical disorder elements



# Contributions

- **UrbanPhysicalDisorder dataset**
- **Physical disorder matters**
- **LLMs-based method to interpret counterfactuals**

# PlacePulse dataset

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# PlacePulse dataset

Which place looks livelier ?



For this question: **362,708** clicks collected      Goal: **500,000** clicks

[SEE REAL-TIME RANKINGS](#)

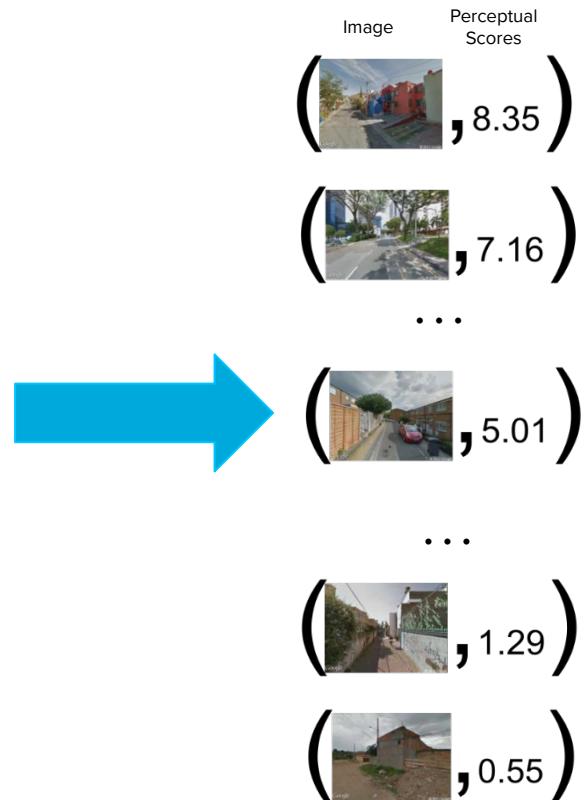
RANK	CITY	CLICKS	TREND	RANK	CITY	CLICKS	TREND
1	Washington DC	6296		54	Cape Town	16228	
2	London	17982		55	Belo Horizonte	12728	
3	New York	22424		56	Gaborone	4717	

- 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.

# Cities included



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High safety scores images



# Rio de Janeiro samples



Scores from 0 to 10

# **Urban Physical Disorder**

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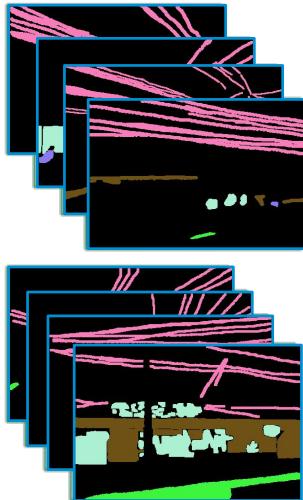
# Urban physical disorder annotations

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

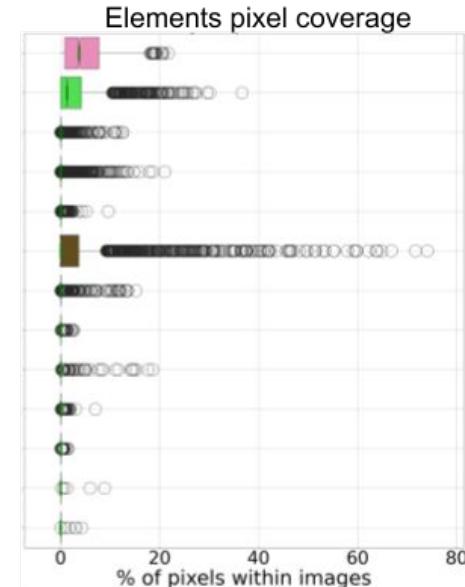
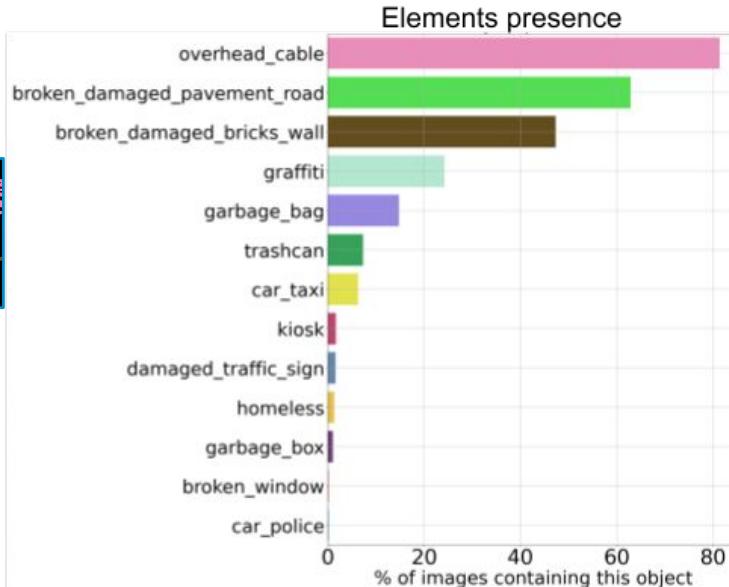


# Urban physical disorder annotations

Manual annotations



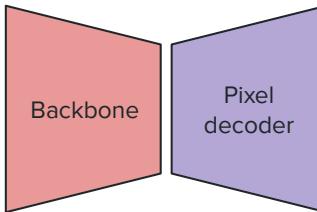
(a)



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

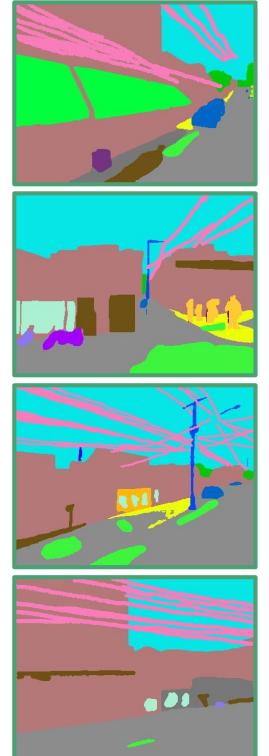
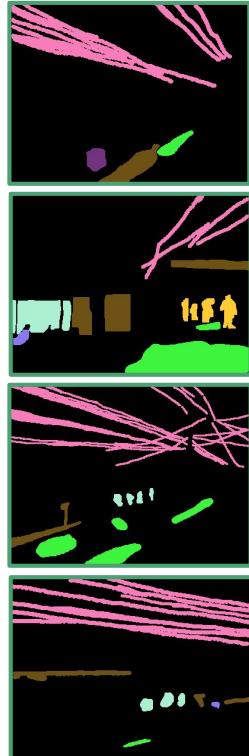
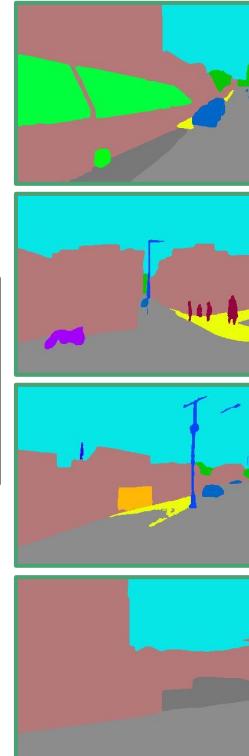
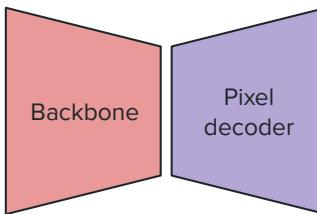
# ADE20K

- We use OneFormer pre-trained model



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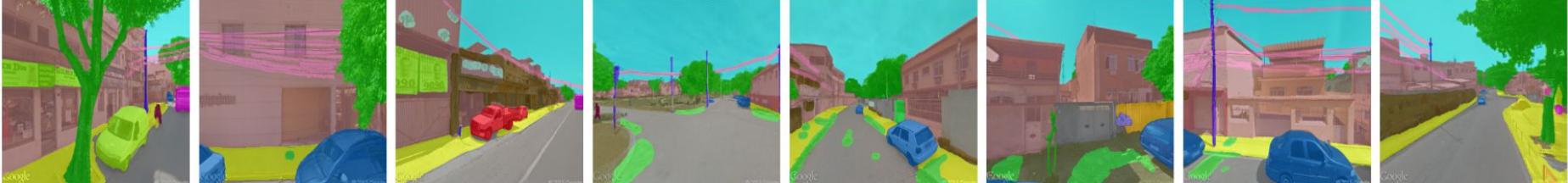


# UPD + ADE20K

50f5ebcdfdc9f065f0008589 50f5ec41fdc9f065f00088cb 50f5ec44fdc9f065f0008900 50f5eaaefdc9f065f0007c15 50f5eb1efdc9f065f0007fdc 50f5eb27fdc9f065f0008081 50f5ead3fdc9f065f0007d9f 50f5eb19fdc9f065f0007f7f  
safety not safety safety safety not safety safety not safety safety



50f5ea5efdc9f065f0007ae3 50f5ebcef9f065f00085a3 50f5ec36fdc9f065f00087f3 50f5eb3fdc9f065f00080bb 50f5eb24fdc9f065f0008057 50f5eae9fdc9f065f0007deb 50f5ead6fdc9f065f0007ddb 50f5ec15fdc9f065f00086e2  
safety safety not safety not safety not safety safety not safety



50f5ec15fdc9f065f00086e1 50f5ebcf5fdc9f065f00084d4 50f5eab0fdc9f065f0007c3f 50f5ebcffdc9f065f00085b8 50f5eaaadf9f065f0007c01 50f5ebcef9f065f000859b 50f5ebaffdc9f065f0008499 50f5eb18fdc9f065f0007f6e  
not safety safety safety safety safety not safety not safety not safety

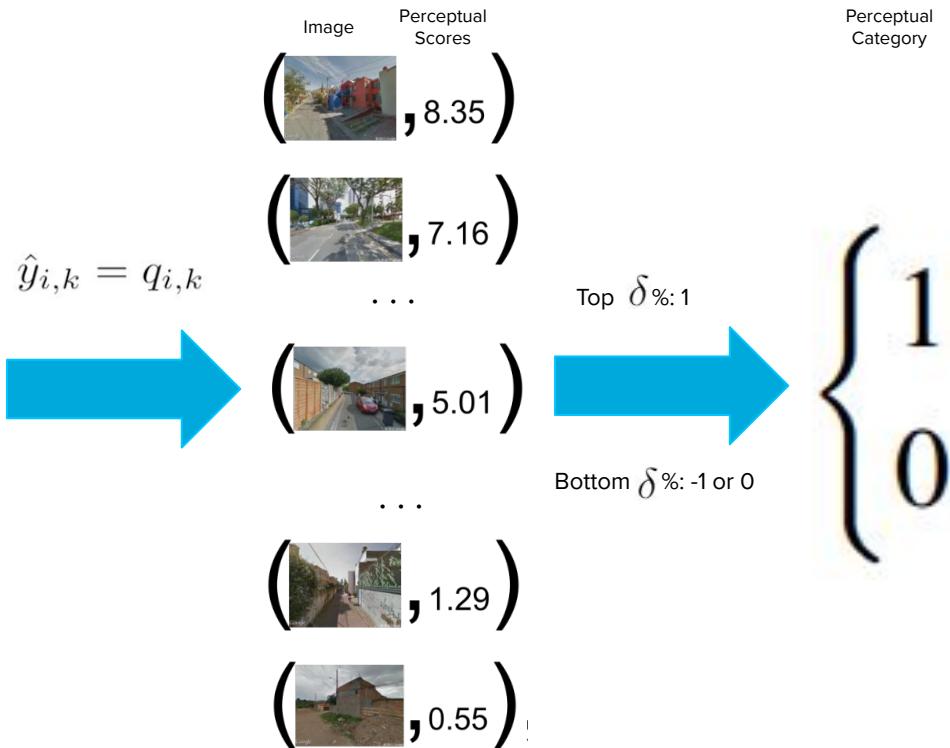


# Experiments

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# Labeling

left	right	winner
		draw
		left
		right
⋮	⋮	⋮
		right
		left



# 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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# New groups + physical disorders

Category	# classes	class name
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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))

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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- Pixel ratios: The images are represented as pixel ratio vectors (between 0 and 1)

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	<b>0.75</b>
		safe	0.75	0.69	<b>0.72</b>

# **Counterfactuals & LLMs**

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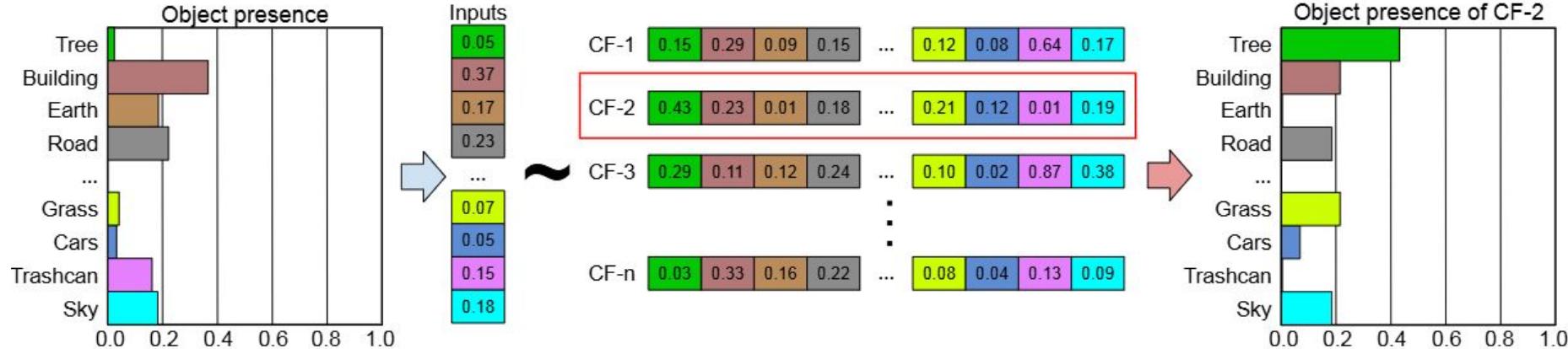
# CounterFactuals

We analyze the best case

Setting	Categories	Perception	Metrics		
			Precision	Recall	F-1
ADE20K (150 classes)	not safe	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	<b>0.75</b>
		safe	0.75	0.69	<b>0.72</b>

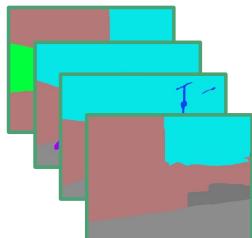
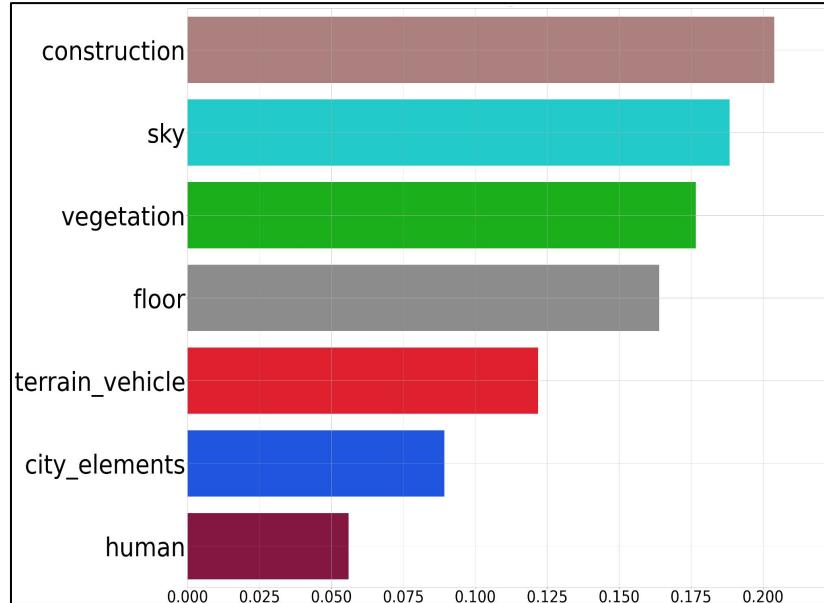
# Counterfactuals

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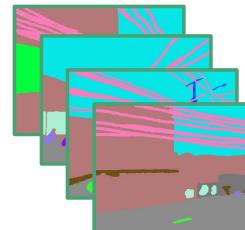
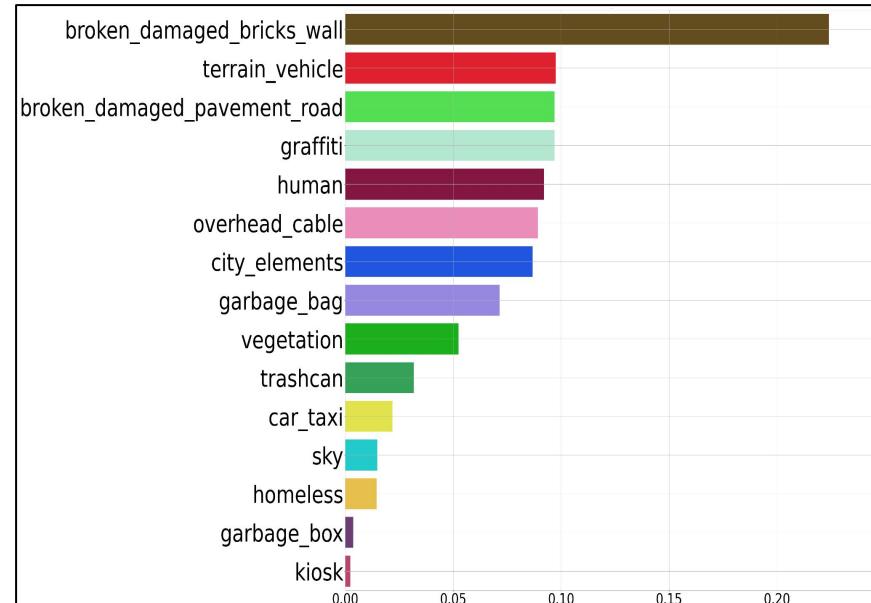
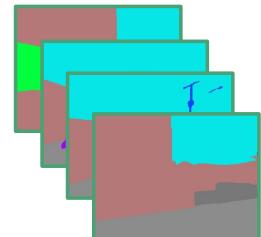
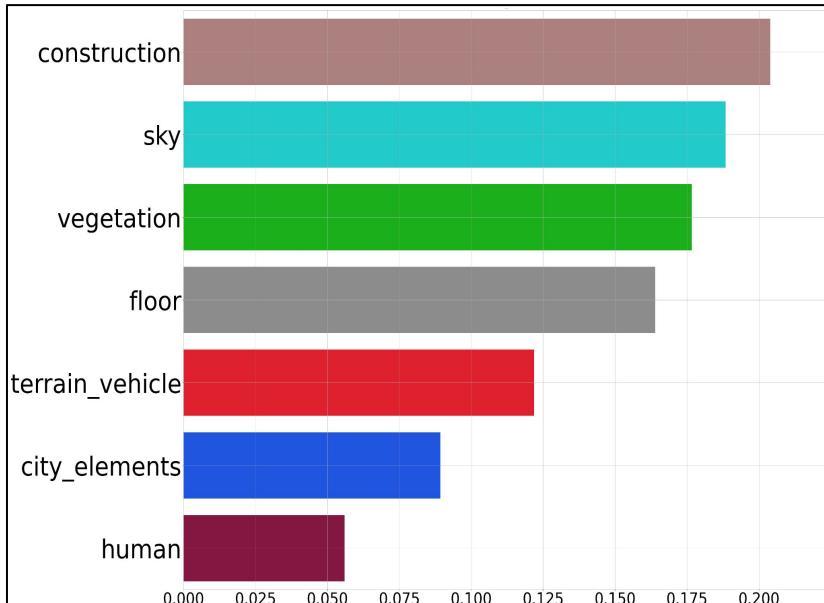


- Dice-ML generates counterfactuals
- Identify what objects should be removed or increased

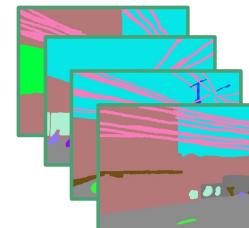
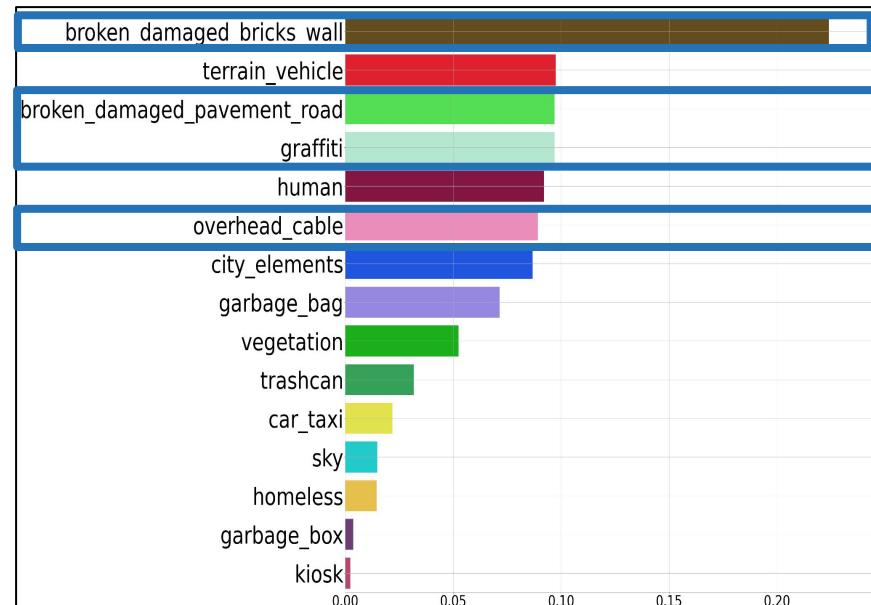
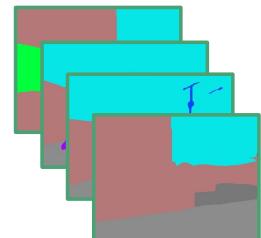
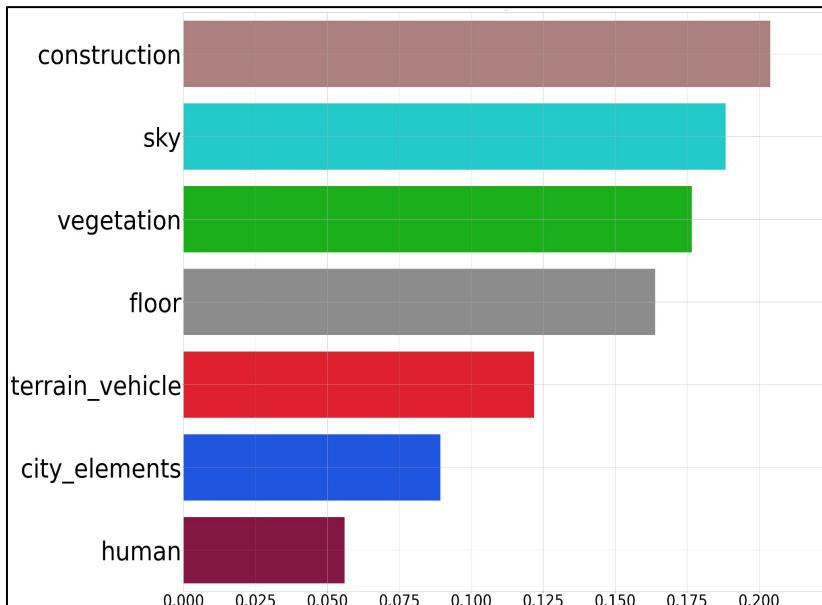
# Counterfactuals



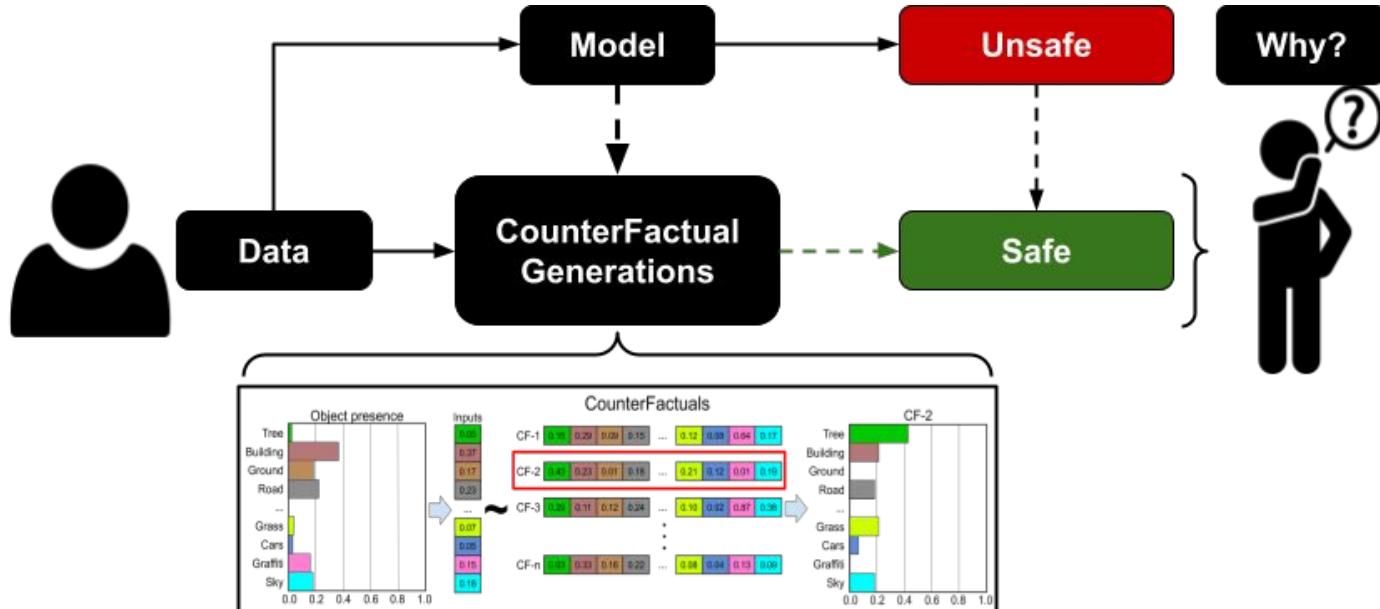
# Counterfactuals



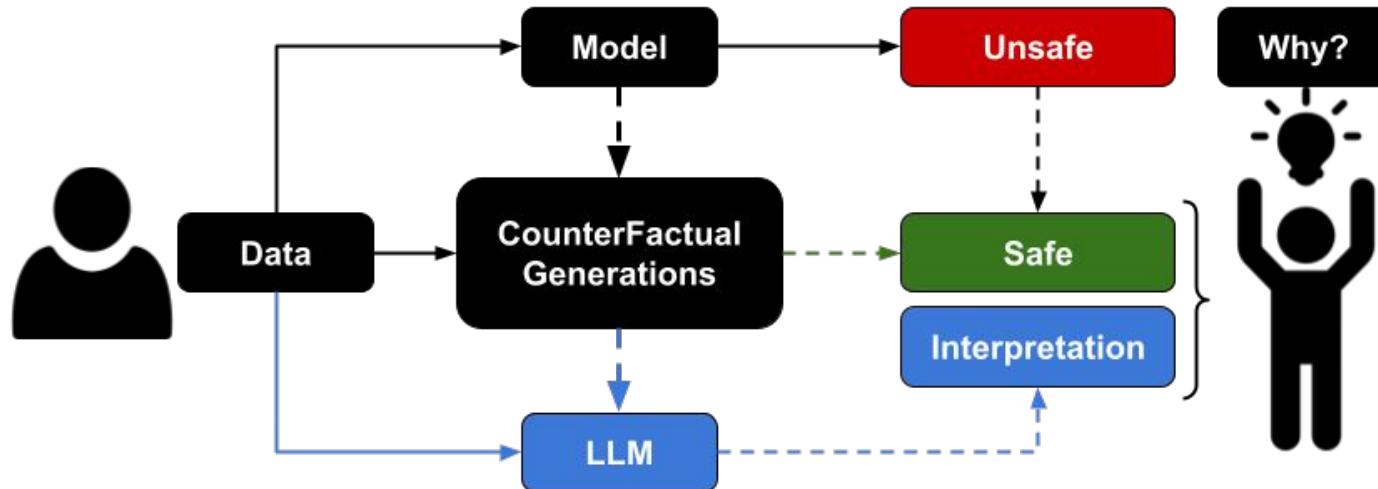
# Counterfactuals: Most relevant objects changed



# CounterFactual explanations



# LLM interpretations



# LLM interpretations: unsafe sample

Image	
	
$\Delta$ 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	
$\Delta$ 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	
	 Google © 2015 Google
$\Delta$ 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



Google  
© 2015 Google



Google  
© 2015 Google



Google  
© 2015 Google

$\Delta$  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

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# 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:** translating non-human-readable vectors into natural language can improve the understanding of which elements should be modified.

# **THANKS!**

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