Understanding Safety Based on Urban Perception

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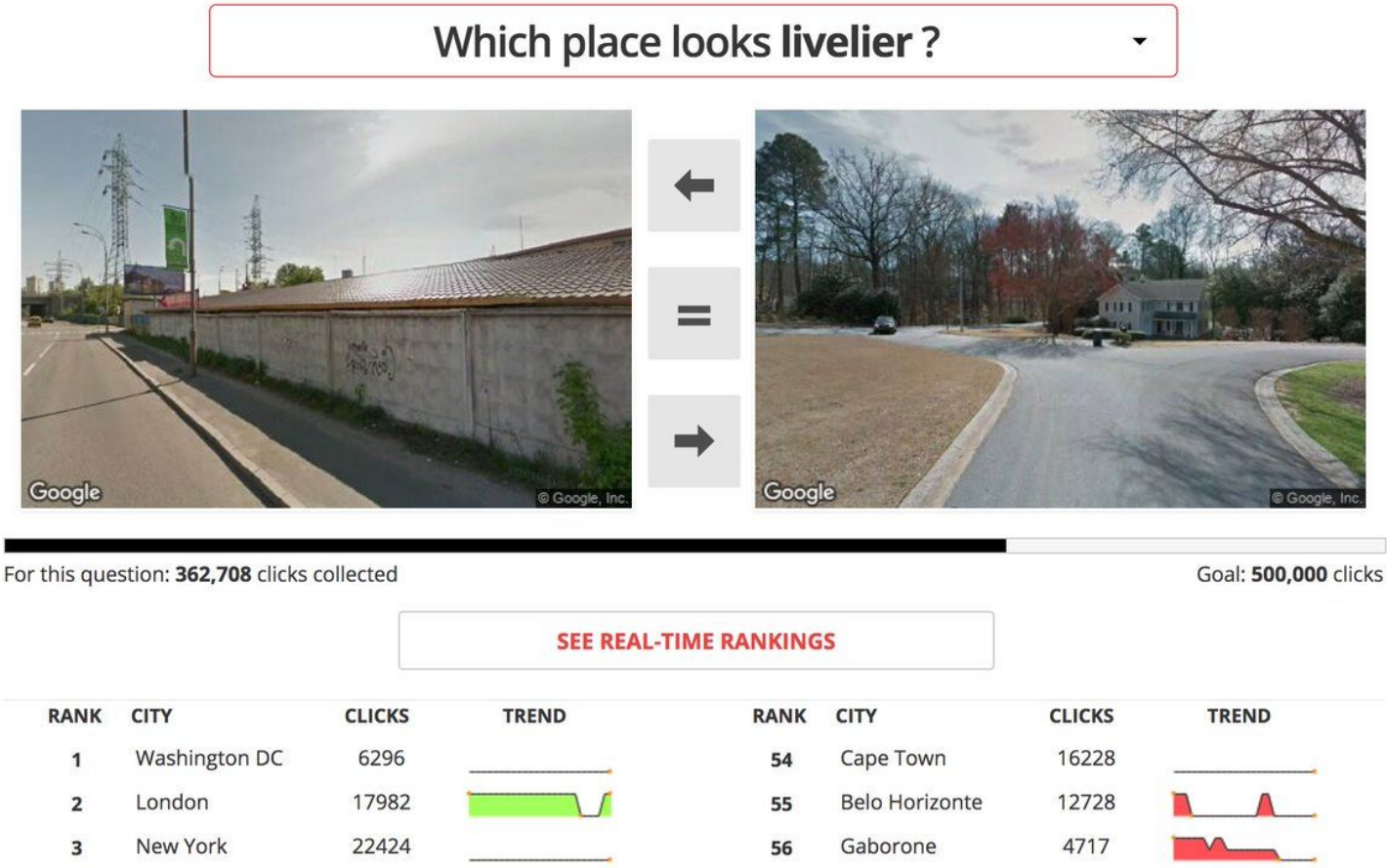
Place Pulse



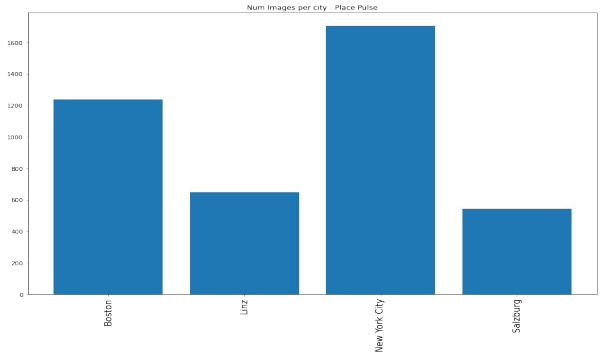
http://pulse.media.mit.edu/

* Comparisons were made using two random images from random cities.

Place Pulse Dataset

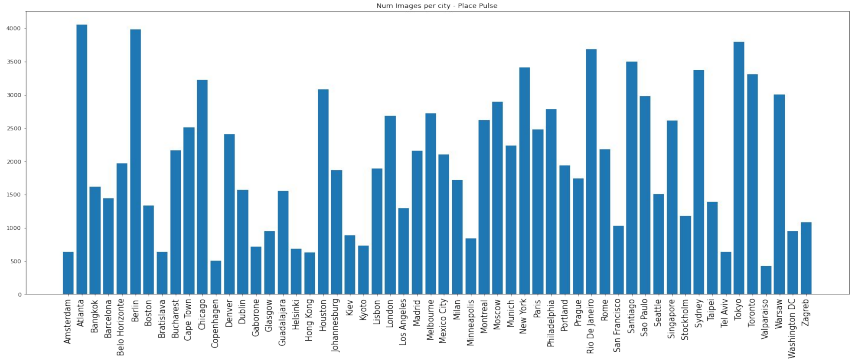
Place Pulse 1.0:

- 73 806 Comparisons, 4 136 images
- 2 Countries (US y Austria)
- 4 cities: New York City, Boston, Linz and Salzburg
- 3 categories: Safe, Wealth and Unique



Place Pulse 2.0:

- 1 223 649 Comparisons, 111 390 images
- 32 countries
- 56 cities
- 6 categories: Safe, Wealth, Depress, Beautiful, Boring, and Lively



* **Remember:** We will focus in **Place Pulse 2.0** only.

Dataset sample: Set of comparisons*

left_id	right_id	winner	left_lat	left_long	right_lat	right_long	category
513d7e23fdc9f	513d7ac3fdc9f	equal	40.744156	-73.93557	-33.52638	-70.591309	depressing
513f320cfdc9f	513cc3acfdc9f	left	52.551685	13.416548	29.76381	-95.394621	safety
513e5dc3fdc9f	5140d960fdc9f	right	48.878382	2.403116	53.32932	-6.231007	lively

* **Remember:** Comparisons were made using two random images from random cities.

Processed sample: Images from Rio de Janeiro - Place Pulse 2.0

Image	ID	Safety	Lively	Wealthy	Beauty	Boring	Depressive
	513d7e23fdc9f	7.42	8.58	6.5	7.3	2.64	1.23
	513f320cfdc9f	6.07	4.97	7.13	8.61	1.67	0.86

* **Note:** We perform the calculation in all categories, but we will focus in safety only.

Dataset Statistics: summary

Place Pulse 1.0				
City	# images	*safe mean*	*wealth mean*	*unique mean*
Linz	650	4.85	5.01	4.83
Boston	1237	4.93	4.97	4.76
New York	1705	4.47	4.31	4.46
Salzburg	544	4.75	4.89	5.04
Total	4136			

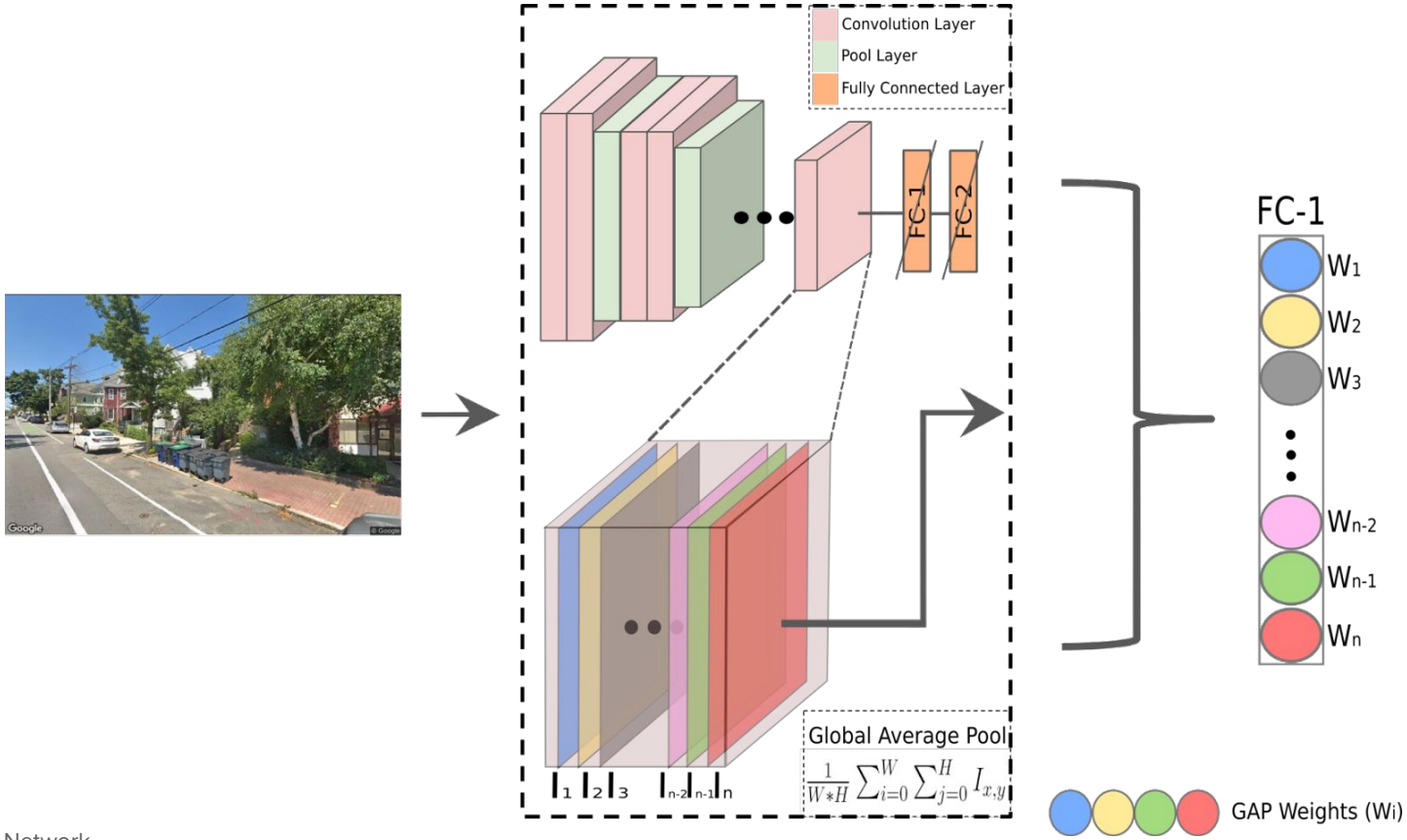
Place Pulse 2.0			
Continent	#countries	#cities	#images
Europe	19	22	38,747
North America	3	17	37504
South America	2	5	12,524
Asia	5	7	11,417
Oceania	1	2	6,097
Africa	2	3	5,101
Total	32	56	111,390

Place Pulse 2.0			
Category	# comparisons	# images	*mean*
Safety	368,926	111,389	5.188
Lively	267,292	111,348	5.085
Beautiful	175,361	110,766	4.920
Wealthy	152,241	107,795	4.890
Depressing	132,467	105,495	4.816
Boring	127,362	106,363	4.810
Total	1,223,649		

Urban Safety Perception

Transfer Learning/Fine-Tuning

Transfer Learning



*VGG16-GAP Network

Processed data: Perceptual scores

left	right	winner
		draw
		left
		right
. . .	. . .	. . .
		right
		left

$$\hat{y}_{i,k} = q_{i,k}$$

I:
(X,Y)

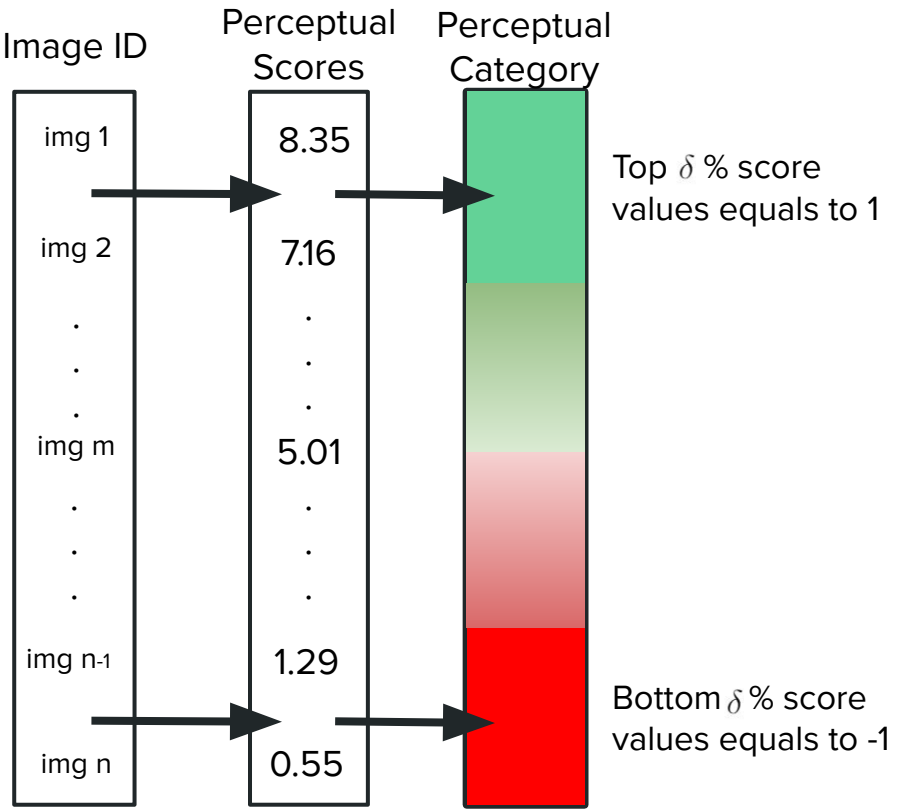
Image	Perceptual Scores
	8.35
	7.16
. . .	
	5.01
. . .	
	1.29
	0.55

Classification Problem

Parametrized by an additional parameter δ

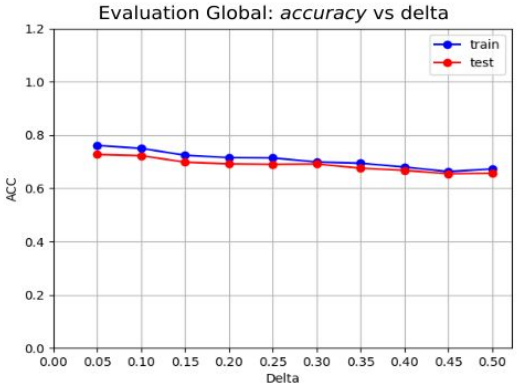
$$y_{i,k} = \begin{cases} 1 & \text{if } (q_{i,k}) \text{in the top } \delta\% \\ \text{-1} & \text{if } (q_{i,k}) \text{in the bottom } \delta\% \end{cases}$$

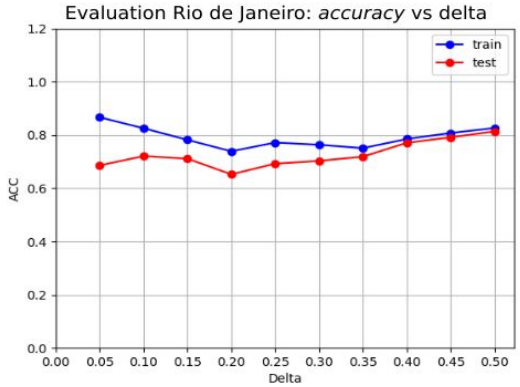
Metrics: ACC, F1, Precision-Recall, and AUC (Area Under Curve). Trained using a 5-Fold cross-validation.

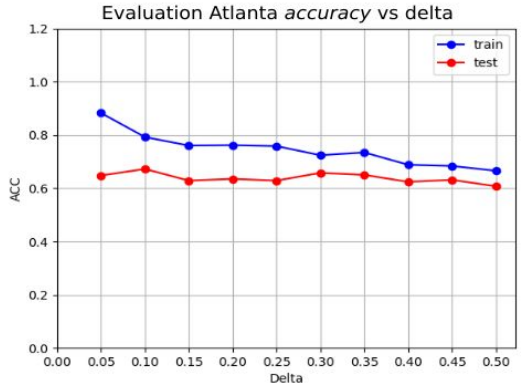


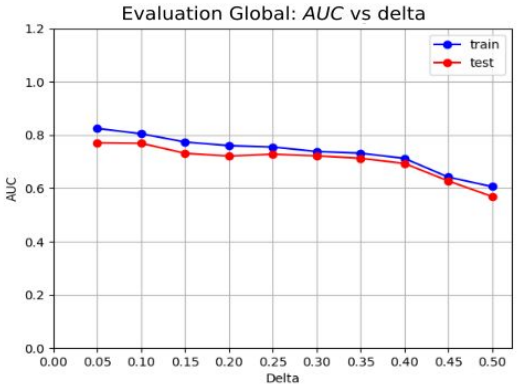
Experiments & Results

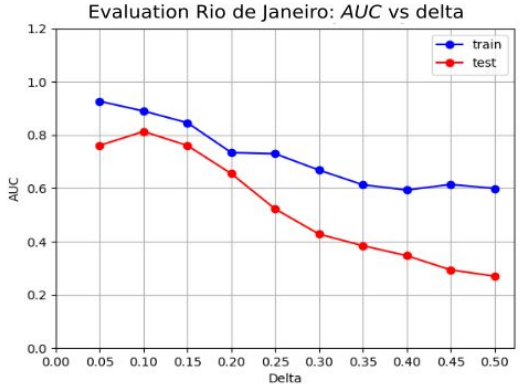
Transfer-Learning models results

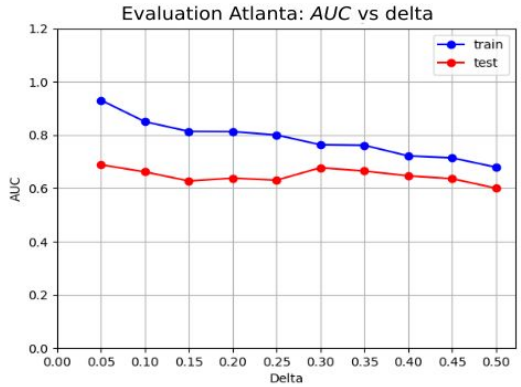












* Results of testing using different values of δ.

Transfer-Learning models results

		auc		*accuracy*		*f1 score*	
Model	Method	train	eval	train	eval	entrena	eval
VGG	*LinearSVC*	63.62	56.50	68.85	65.22	54.78	**49.41**
	Logistic	60.63	**57.52**	67.25	**65.72**	51.42	49.07
	Ridge Classifier	64.72	54.75	69.44	64.38	56.50	49.34
	RBF SVC	45.14	42.42	52.13	52.37	46.93	46.59
VGG_GAP	*LinearSVC*	59.01	**57.93**	66.51	**66.09**	49.52	49.06
	Logistic	58.07	57.57	65.95	65.59	46.06	45.61
	Ridge Classifier	59.20	57.93	66.59	65.89	50.27	**49.76**
	RBF SVC	42.93	41.70	50.25	50.35	47.16	46.75

* **Results of testing using all dataset.**

Transfer-Learning models results

		auc		*accuracy*		*f1 score*	
Model	Method	train	eval	train	eval	entrena	eval
VGG_Places	*LinearSVC*	64.44	57.14	69.48	65.79	56.39	51.20
	Logistic	61.74	**58.35**	68.16	**66.44**	53.77	**51.28**
	Ridge Classifier	65.20	55.76	69.84	64.86	57.56	50.67
	RBF SVC	47.32	45.25	56.56	55.69	44.78	44.21
VGG_GAP_Places	*LinearSVC*	60.26	**59.76**	67.38	**66.96**	51.65	51.04
	Logistic	59.40	58.97	66.81	66.62	49.16	48.90
	Ridge Classifier	60.45	59.15	67.45	66.94	52.23	**51.53**
	RBF SVC	44.40	42.47	52.59	52.54	43.39	45.05

* **Results of testing using all dataset.**

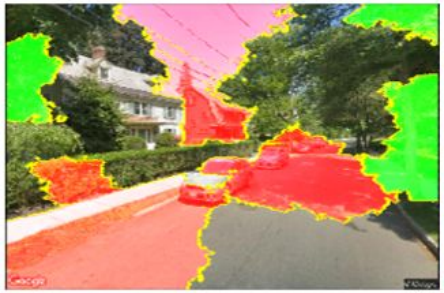
LIME vs Grad-CAM++

(a) Score: 8.35

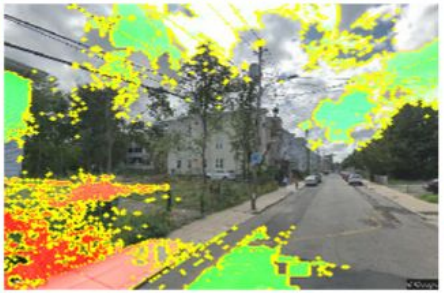
(b) Score: 4.22

(c) Score 1.06

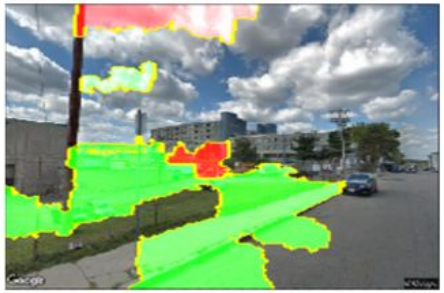
LIME vs Grad-CAM++



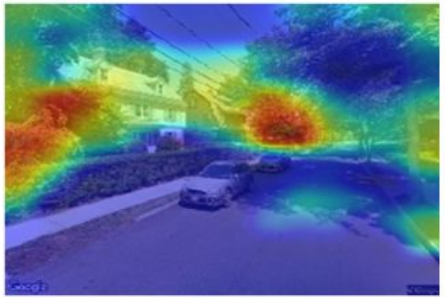
(d) Prediction: safe



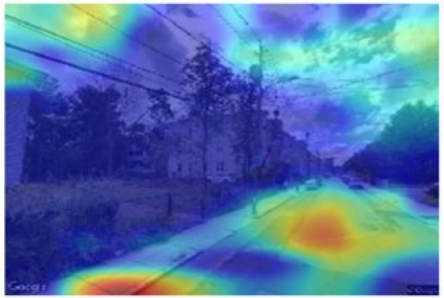
(e) Prediction: not safe



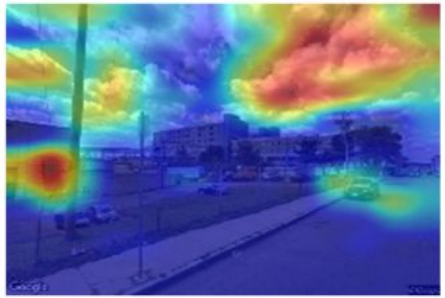
(f) Prediction: not safe



(g) Prediction: safe



(h) Prediction: not safe



(i) Prediction: not safe

Questions?