

# Deep Learning Techniques in Urban Security Perception Analysis

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**FONDECYT**  
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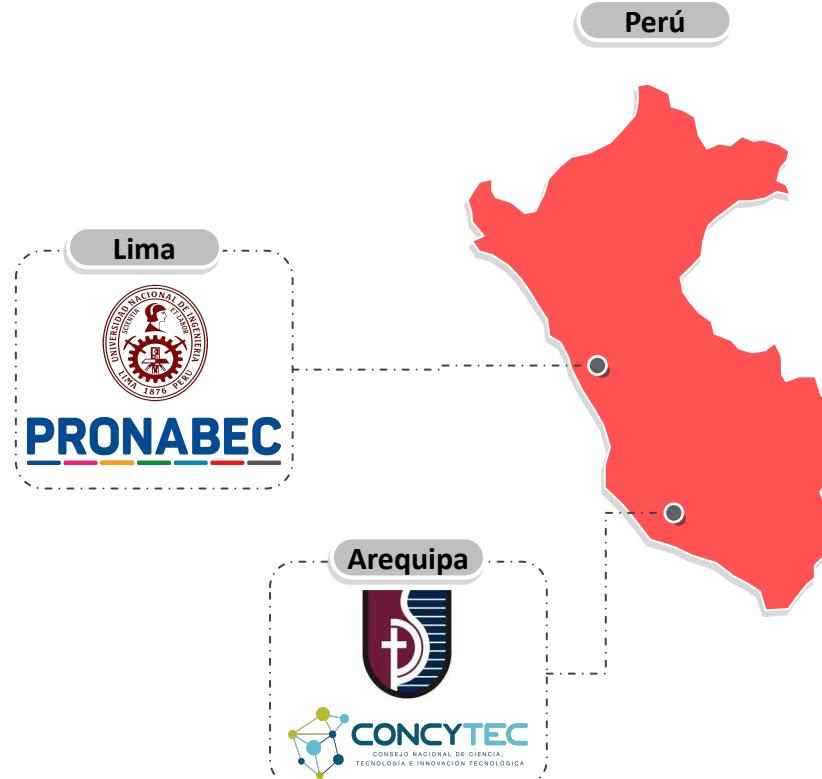
**FGV**  
FUNDAÇÃO  
GETULIO VARGAS

**EMAp**  
ESCOLA DE  
MATEMÁTICA  
APLICADA

# About me



M.Sc. Felipe A. Moreno  
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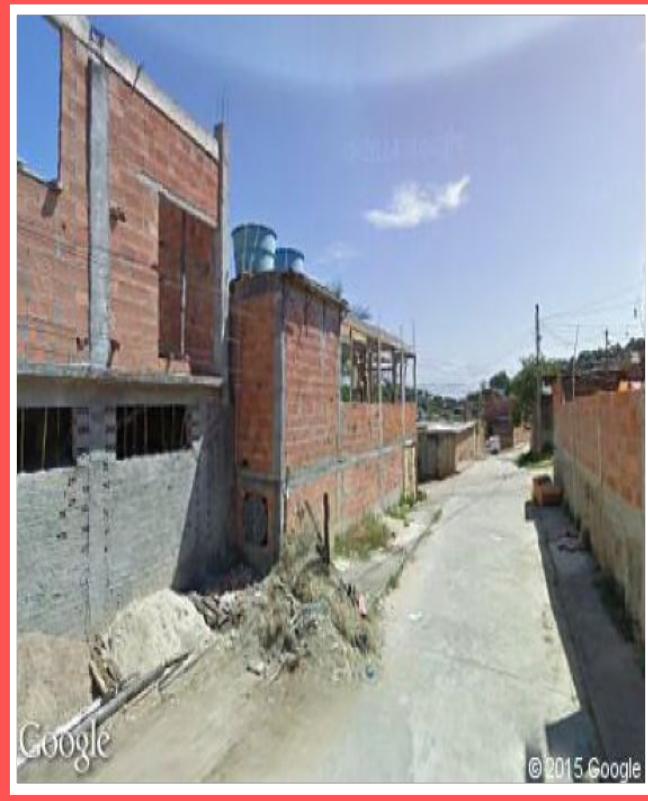
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# Motivation

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# Which one looks safer?



Bangú (RJ)



City Center (RJ)

# Place Pulse

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## 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	

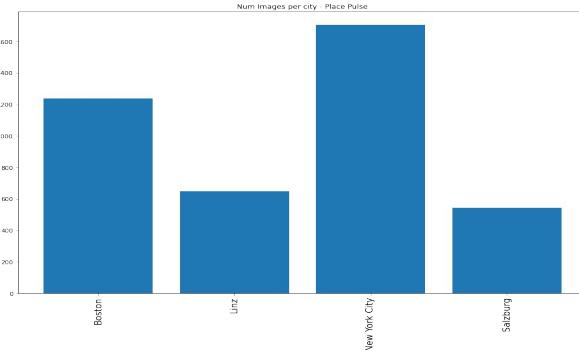
<http://pulse.media.mit.edu/>

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

# Place Pulse Dataset

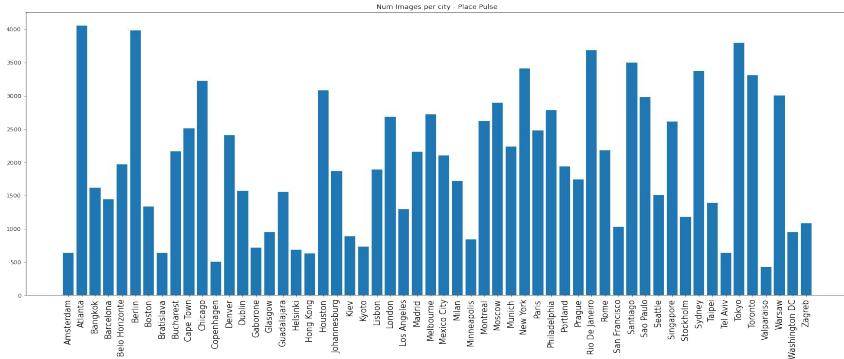
## Place Pulse 1.0:

- 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

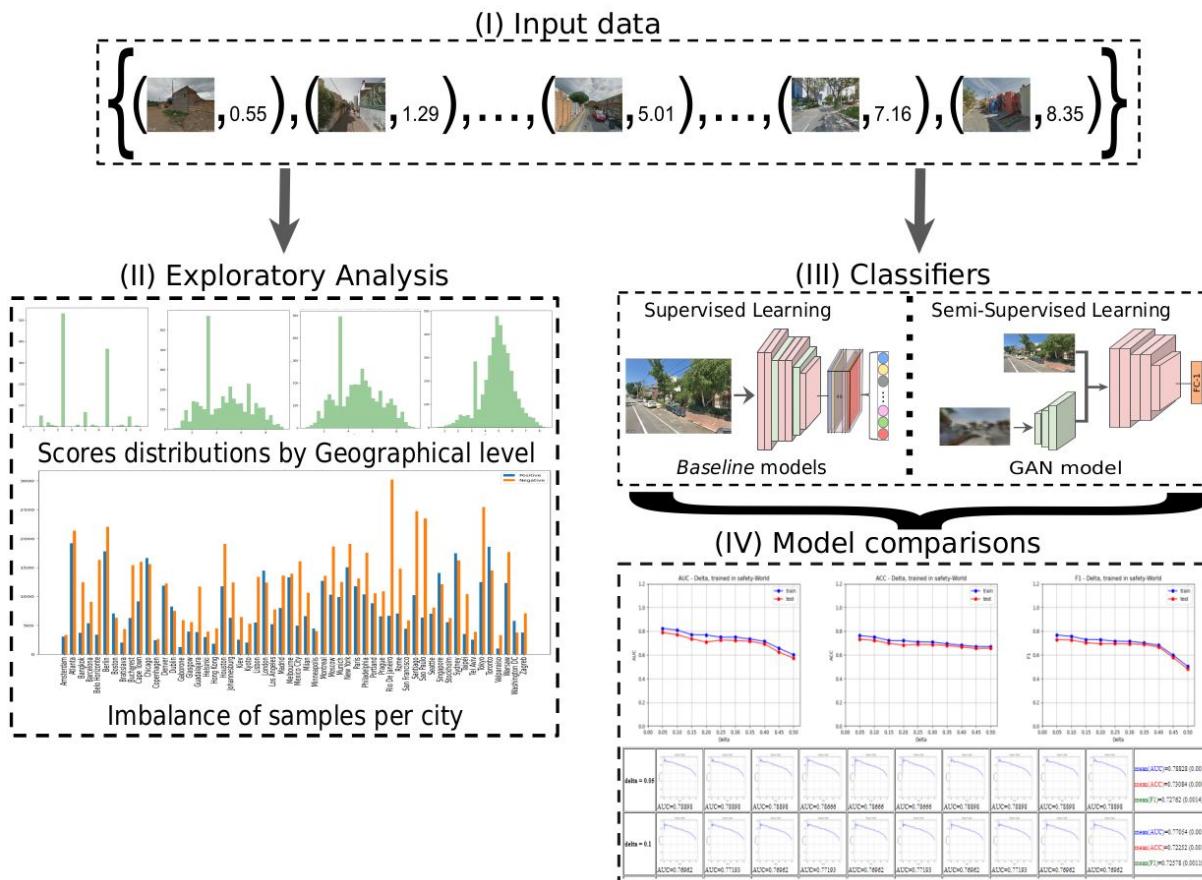


\* Remember: We will focus in **Place Pulse 2.0** only.

# Methodology

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# Pipeline



# Data Pre-processing

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# 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	513cc3acfcd9f	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.

# Pre-processing Comparisons

## Perceptual Scores Approach

\*Nassar et al, "The evaluative image of the city", 1990

$$W_i = \frac{w_i}{w_i + d_i + l_i}$$

$$L_i = \frac{l_i}{w_i + d_i + l_i}$$

\*

$$q_{i,k} = \frac{10}{3} \left( W_{i,k} + \frac{1}{n_{i,k}^w} \left( \sum_{j_1} W_{j_1,k} \right) - \frac{1}{n_{i,k}^l} \left( \sum_{j_2} L_{j_2,k} \right) + 1 \right)$$

## Rank Images Approach

\*\*Minka et al, "TrueSkill 2: An improved Bayesian skill rating system", 2018

$$\mu_x \leftarrow \mu_x + \frac{\sigma_x^2}{c} \cdot f \left( \frac{(\mu_x - \mu_y)}{c}, \frac{\varepsilon}{c} \right)$$

$$\mu_y \leftarrow \mu_y - \frac{\sigma_y^2}{c} \cdot f \left( \frac{(\mu_x - \mu_y)}{c}, \frac{\varepsilon}{c} \right)$$

$$\sigma_x^2 \leftarrow \sigma_x^2 \cdot \left[ 1 - \frac{\sigma_x^2}{c} \cdot g \left( \frac{(\mu_x - \mu_y)}{c}, \frac{\varepsilon}{c} \right) \right]$$

$$\sigma_y^2 \leftarrow \sigma_y^2 \cdot \left[ 1 - \frac{\sigma_y^2}{c} \cdot g \left( \frac{(\mu_x - \mu_y)}{c}, \frac{\varepsilon}{c} \right) \right]$$

$$c^2 = 2\beta^2 + \sigma_x^2 + \sigma_y^2$$

\*\*

$$q_{i,k} = \frac{10}{c_{max,k}} (c_{i,k})$$

# Perceptual Score Approach

$$W_i = \frac{w_i}{w_i + d_i + l_i}$$

$$L_i = \frac{l_i}{w_i + d_i + l_i}$$

$$q_{i,k}^* = \frac{10}{3} \left( W_i + \frac{1}{w_i} \left( \sum_{k_1=1}^{w_i} V_w(k_1) \right) - \frac{1}{l_i} \left( \sum_{k_2=1}^{l_i} V_l(k_2) \right) + 1 \right)$$

Salesse et. al, "The Collaborative Image of The City: Mapping the Inequality of Urban Perception", 2013

\*Nassar et al, "The evaluative image of the city", 1990

# 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	<i>safe mean</i>	<i>wealth mean</i>	<i>unique mean</i>
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			

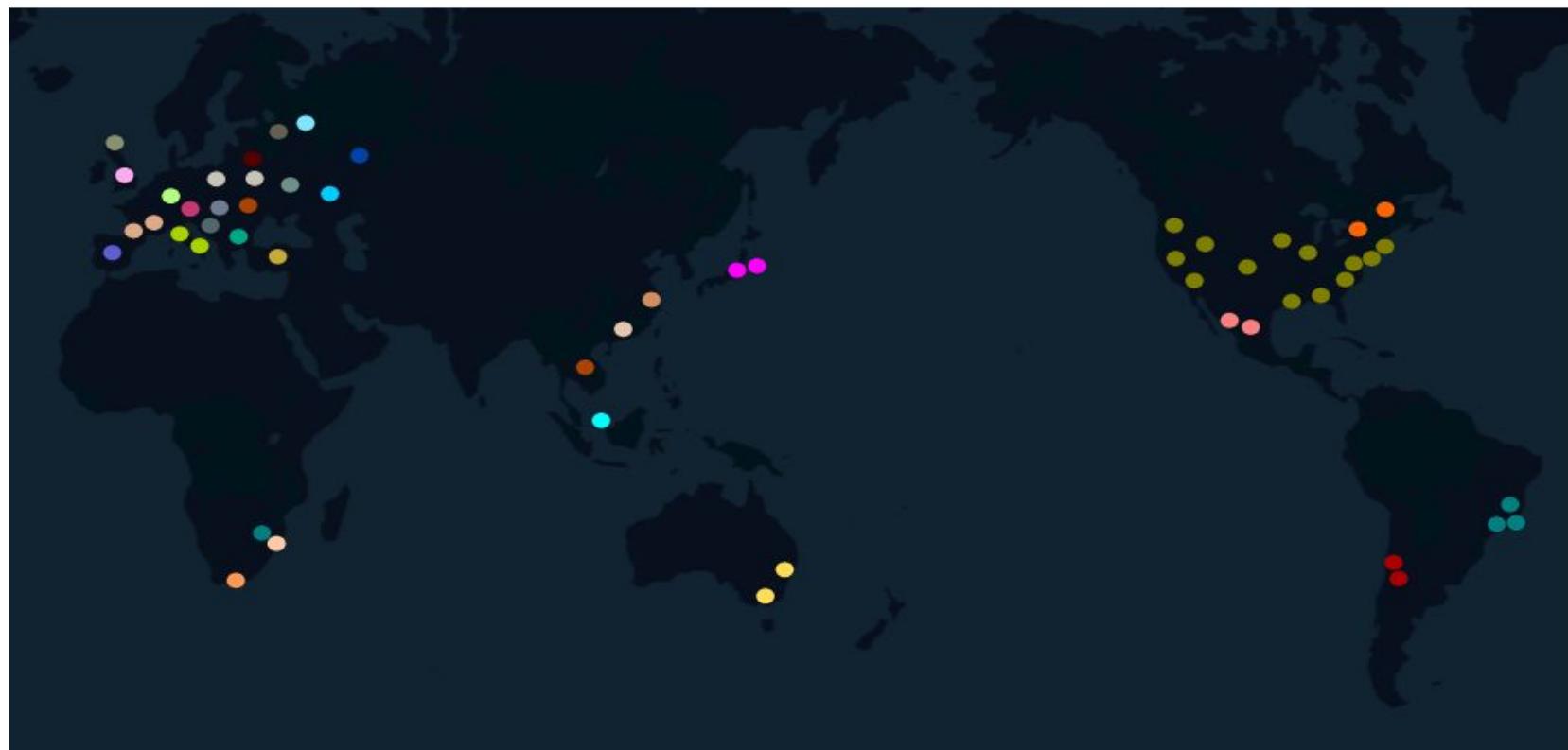
Place Pulse 2.0			
Continent	#countries	#cities	#images
Europe	19	22	38,747
North America	3	17	37504
South America	2	5	12,524
Asia	5	7	11,417
Oceania	1	2	6,097
Africa	2	3	5,101
Total	32	56	111,390

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

# **Exploratory Analysis**

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# Geographical city distribution: Cities included in Place Pulse 2.0



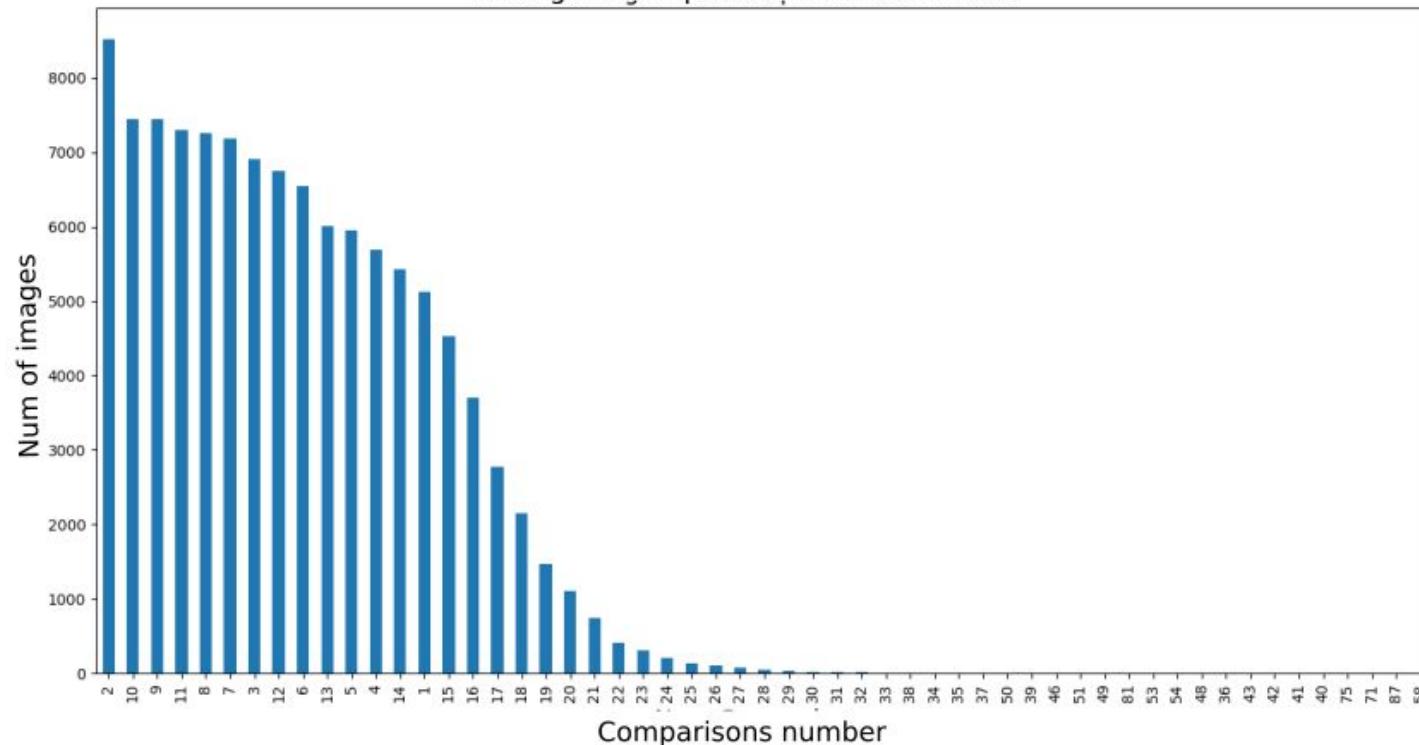
\* Note: Same color means same country.

# Number of images per continent



# Number of comparisons

Average of comparisons number : 9.088



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

# Number of images per geographical level

Place Pulse 2.0				
Category/Level	City	Country	Continent	Global
<i>safety</i>	20,143	45,640	85,890	111,390
<i>lively</i>	14,803	38,216	79,788	111,349
<i>Beautiful</i>	9,410	28,811	66,792	110,767
<i>Wealthy</i>	7,642	24,326	57,780	107,796
<i>Depressing</i>	6,556	21,171	52,504	105,496
<i>Boring</i>	6,148	20,931	52,031	106,364

# **Dataset Limitations**

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# Individual perception

Safe perception

New York\*



Tokyo\*\*



Unsafe perception

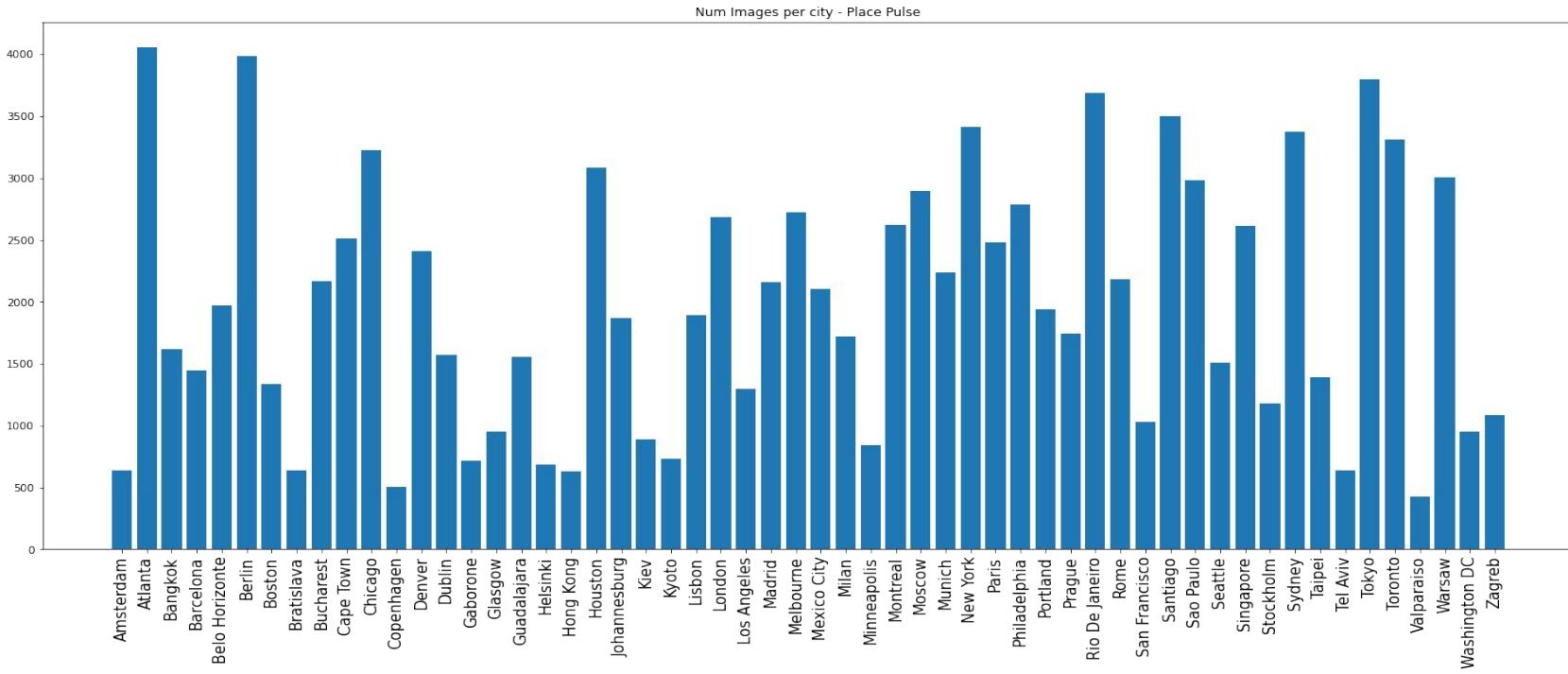


\*<https://www.nytimes.com/2019/08/08/nyregion/newyorktoday/times-square-panic-safety.html#:~:text=Actually%2C%20Times%20Square%20is%20one,23%2C000%20major%20crimes%20were%20recorded.>

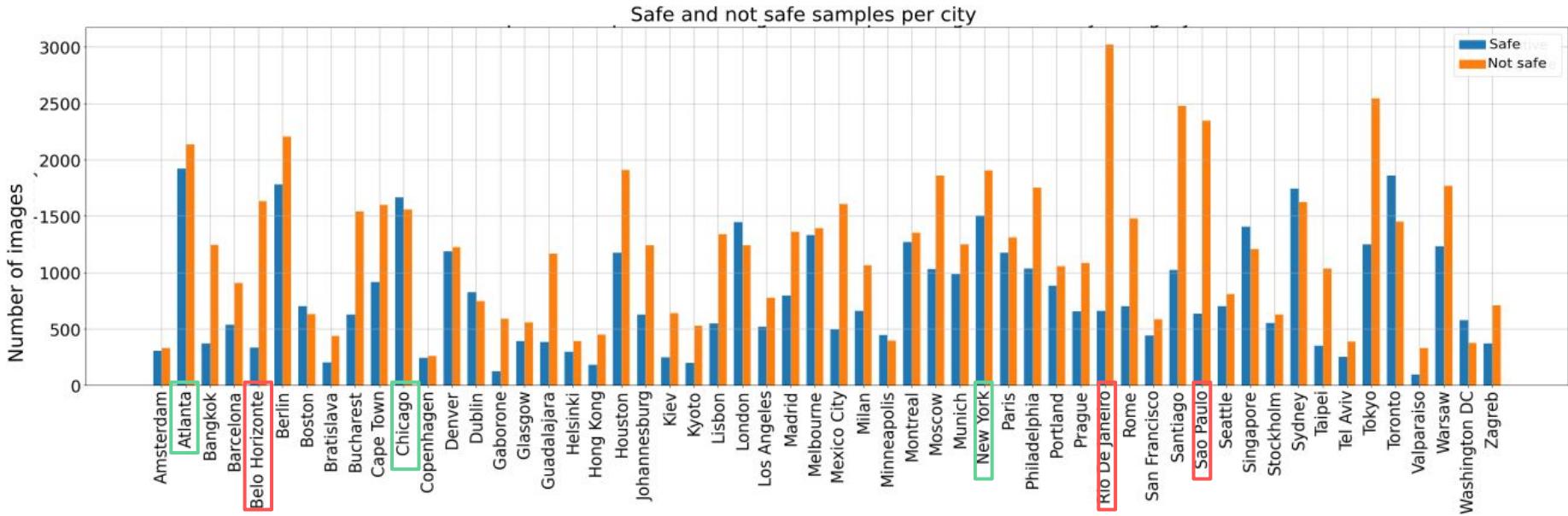
\*\*<https://www.japantimes.co.jp/news/2019/10/04/national/media-national/rip-off-bars-japan-tourist-boom/>

# Lack of samples: Identify city characteristics individually

Place Pulse 1.0 < 4 140 Images & Place Pulse 2.0 < 112 000 Images



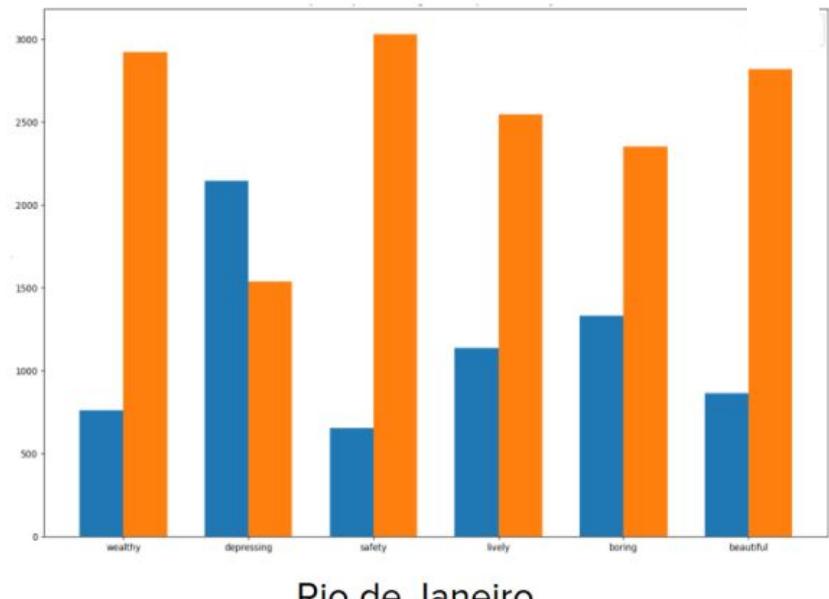
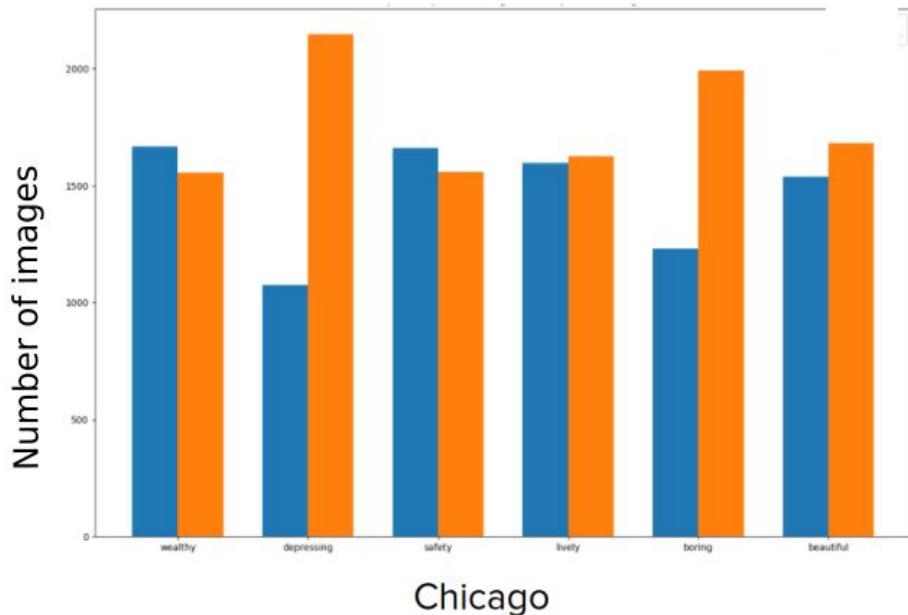
# Imbalance of samples: e.g. Safety category perception



\* Note: Some cities have more “not safe” sample than safe samples. E.g. Brazilian cities.

# Imbalance of samples: e.g. Chicago vs Rio de Janeiro

Imbalance of samples per category in Chicago and Rio de Janeiro



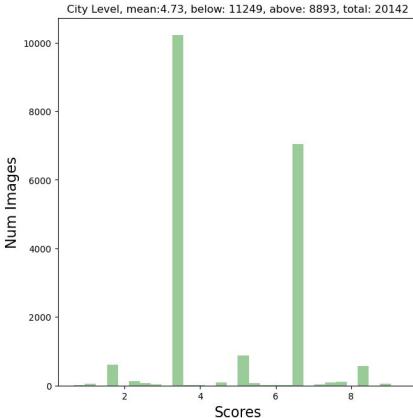
\*Positive Samples: safe, beautiful, wealthy, lively, not depressing, not boring.

\*Negative Samples: not safe, not beautiful, not wealthy, not lively, depressing, boring.

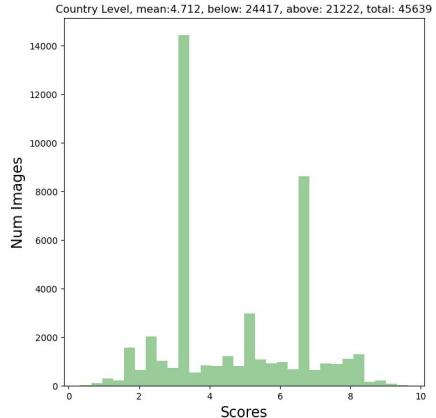
# Non-Reliable Score Distribution

World

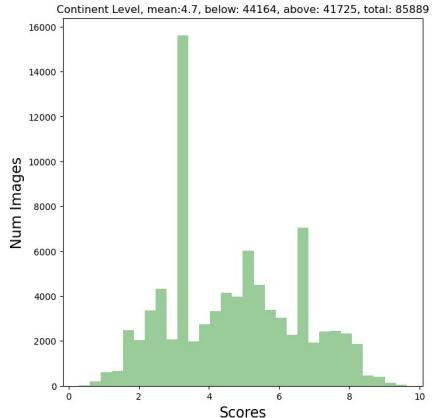
City



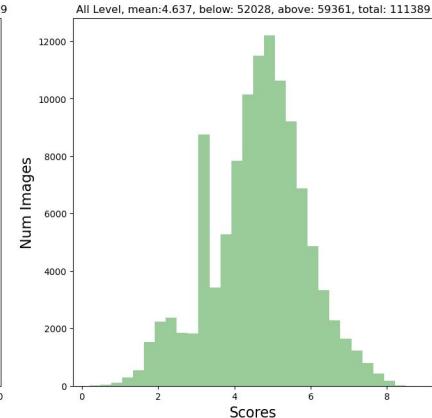
Country



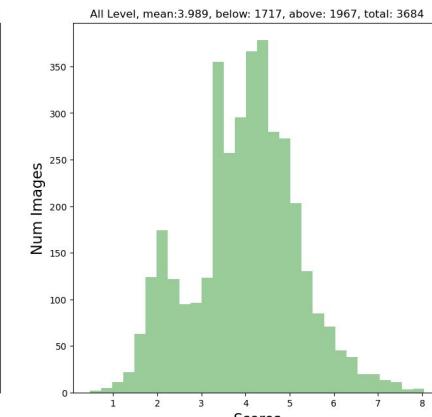
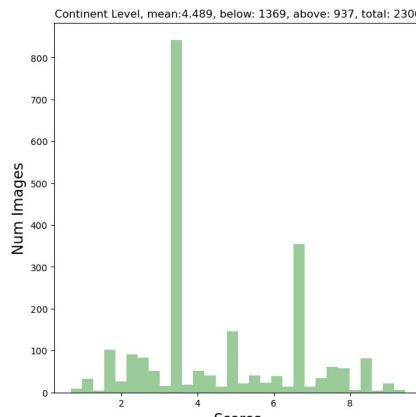
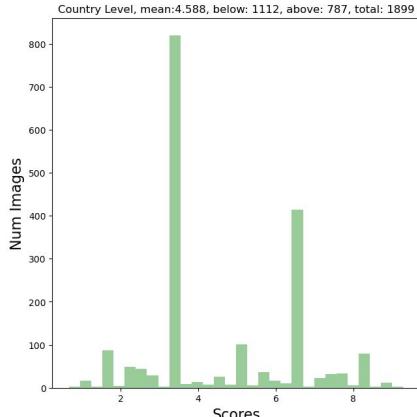
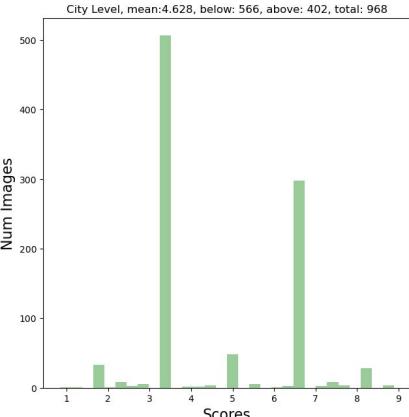
Continent



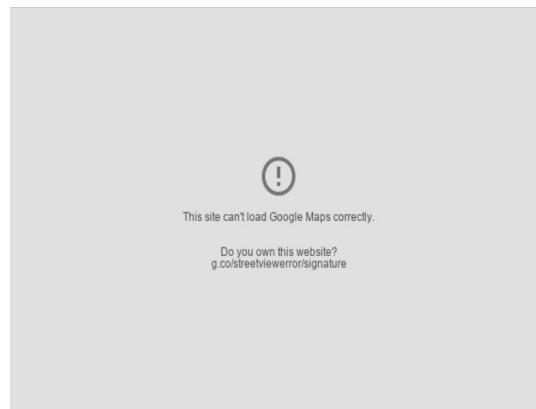
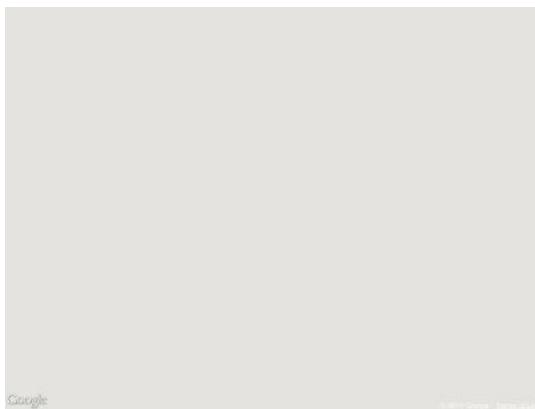
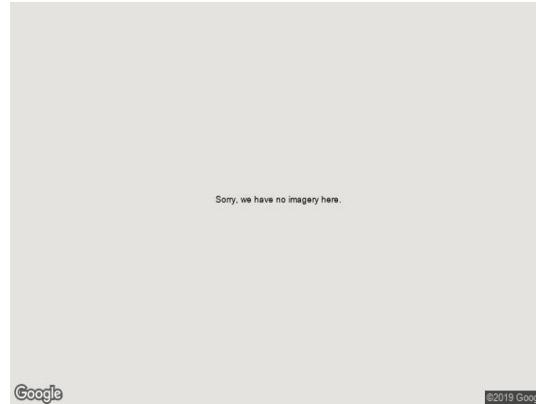
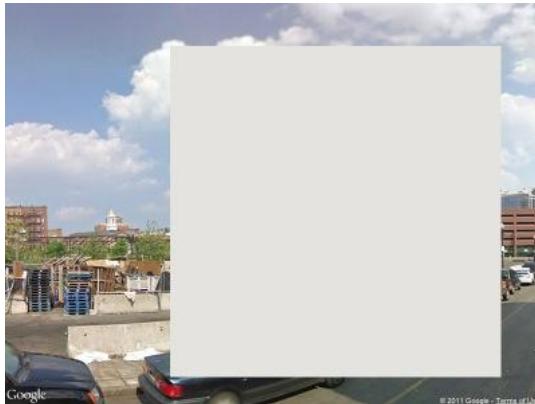
Global



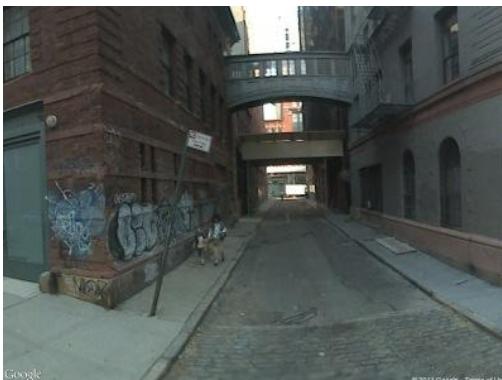
Rio de Janeiro



# Dataset Images: Faulty/Blank/None samples



# Dataset Images: Different Point of View of Sample Images



# Perception changes over time

ID: 3936



ID: 1



2011

2013

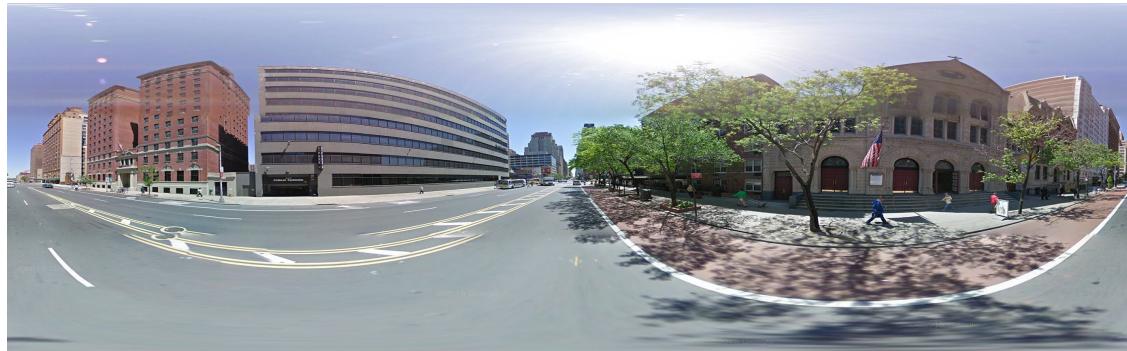
2019

# Different Point of View

Angle: 90



Panoramic



# Urban Safety Perception

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# **Data Analysis & Preparation**

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# Processed data: Perceptual scores

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

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

→

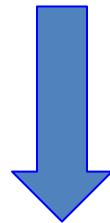
l:  
(X,Y)

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

## Labeling data: From real values to categorical

We define a parameter  $\delta$  which will help to labeling our data.

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



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

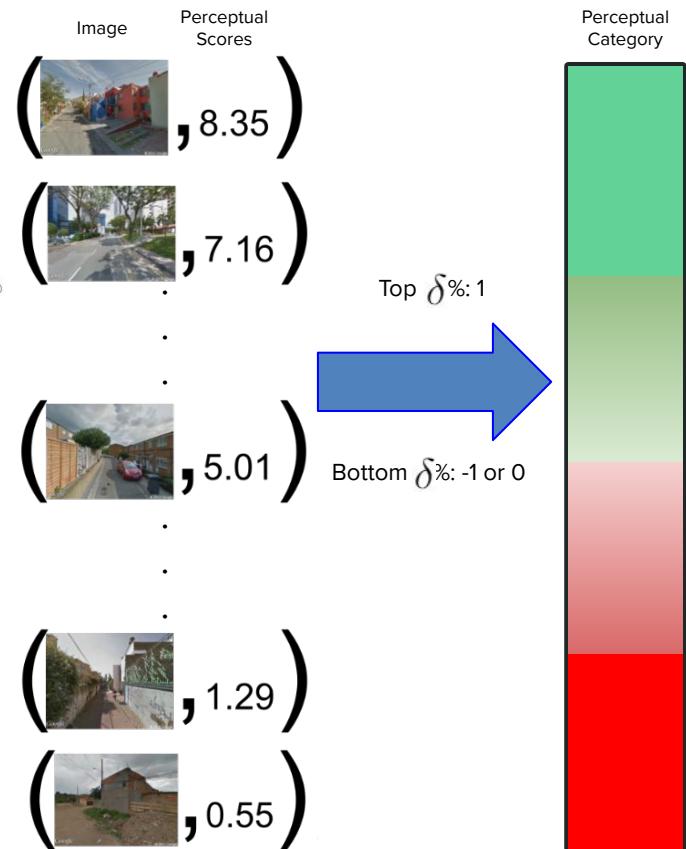
# Processed data: Perceptual classes

left	right	winner
		draw
		left
		right
.	.	.
		right
		left

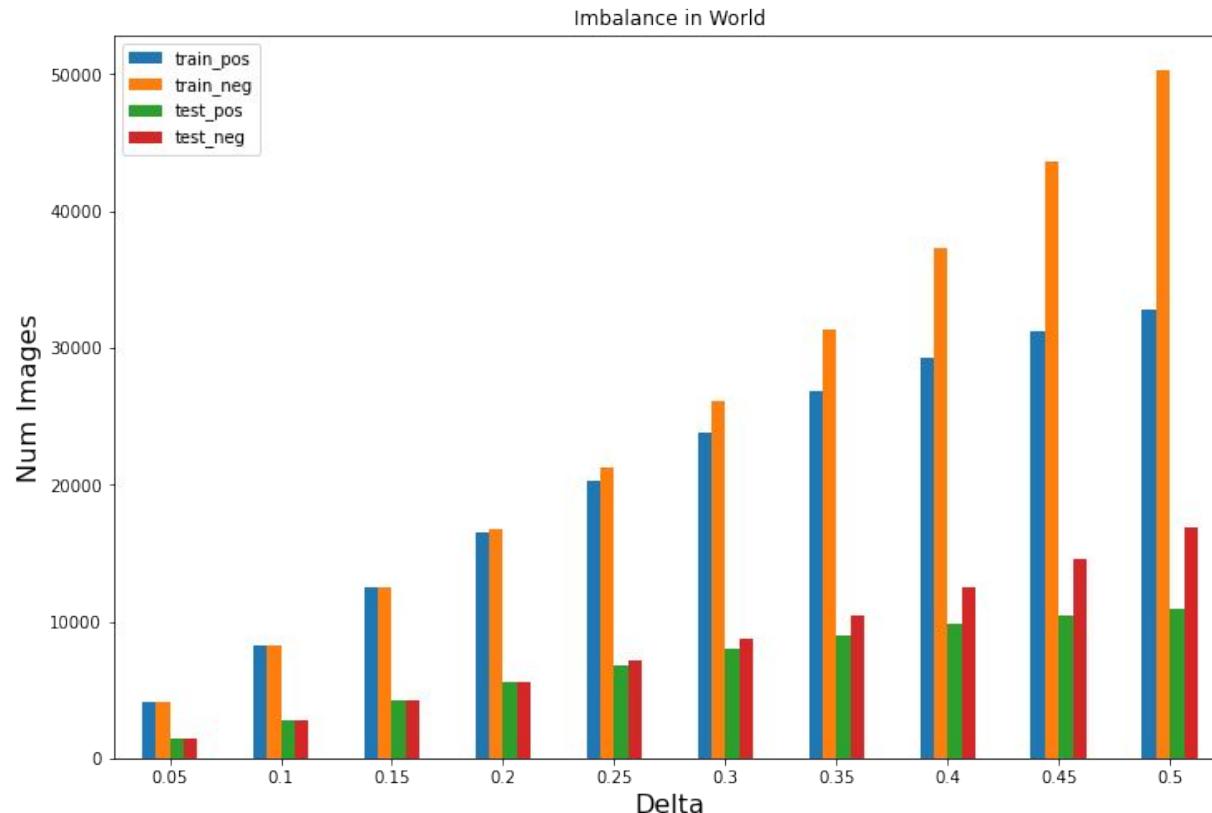
$$y_{i,k} = \begin{cases} 1 & \text{if } (q_{i,k}) \text{ in the top } \delta\% \\ -1 & \text{if } (q_{i,k}) \text{ in the bottom } \delta\% \end{cases}$$



$I: (X, \{1, -1\})$



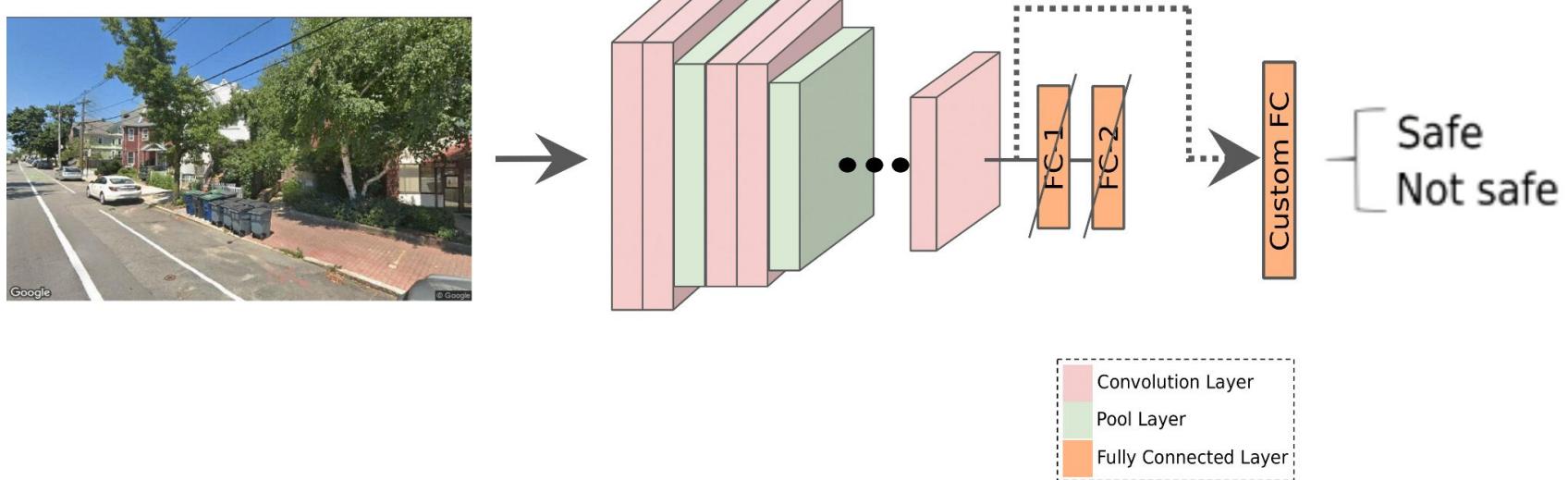
# Evaluating different values of $\delta$



# **Models Configurations**

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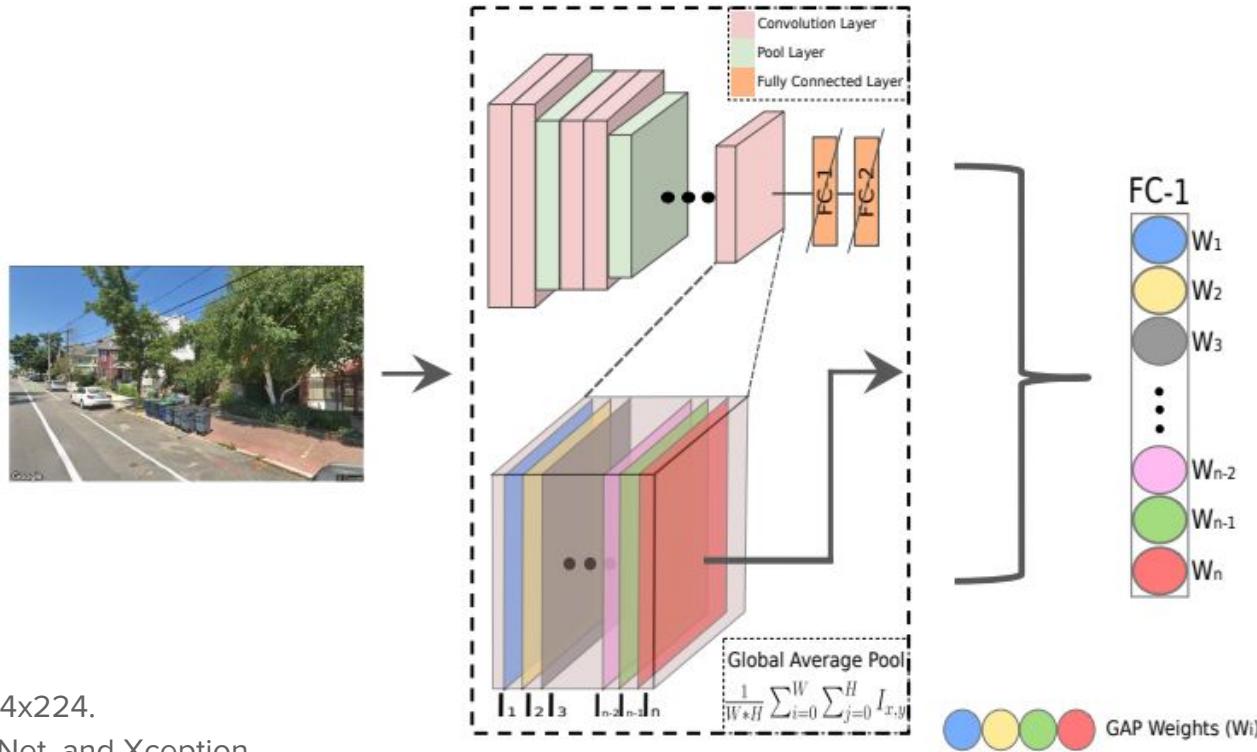
# Baseline model: Transfer Learning (TL) & Fine Tuning (FT)



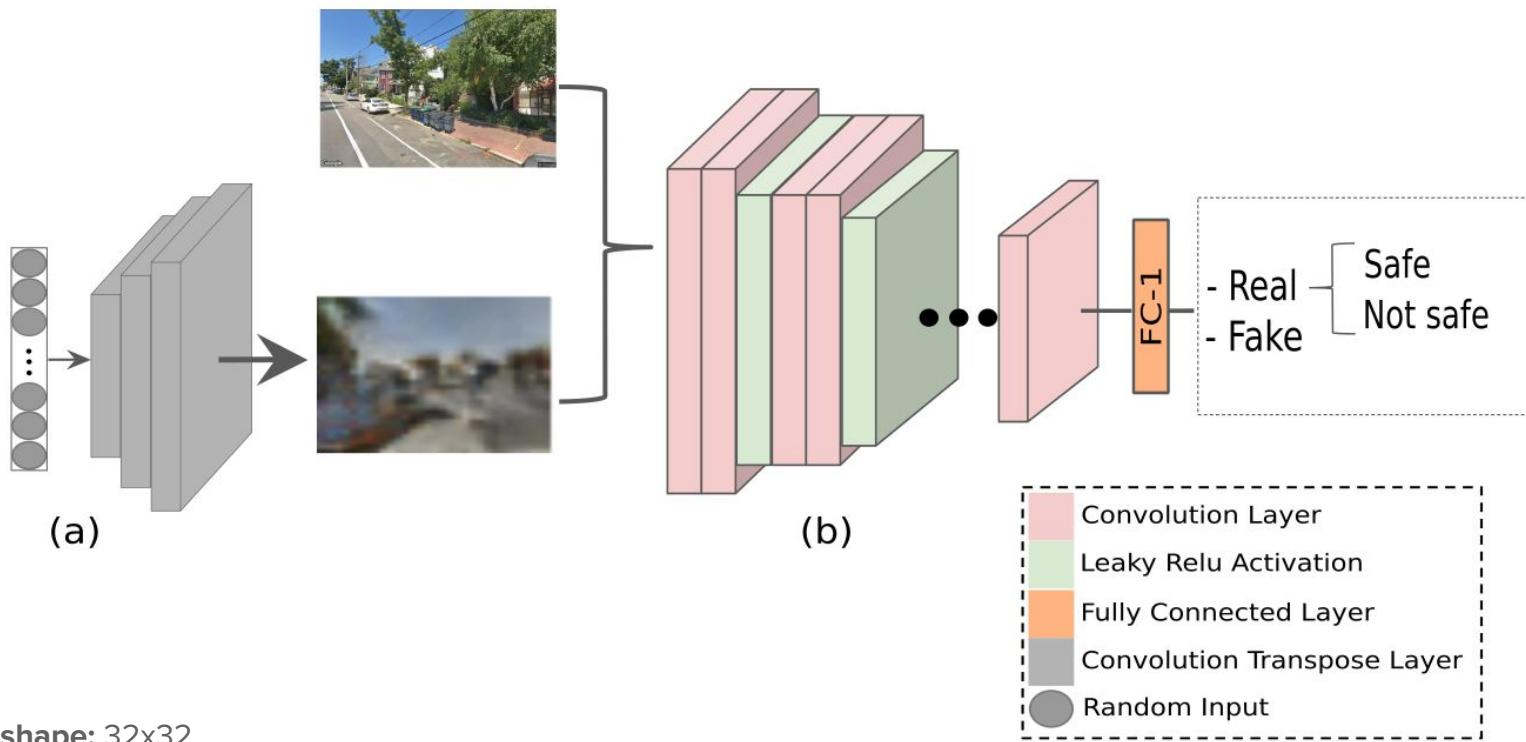
\* Input shape: 224x224.

\* Using VGG, ResNet, and Xception

# Baseline GAP model: Transfer Learning (TL) & Fine Tuning (FT)



# GAN model: Train from scratch discriminator & generator



# GAN model: Discriminator configuration

Discriminator					
Layer	Input	Channels	Kernel size	Stride	Activation
Conv	$32 \times 32 \times 3$	32	$3 \times 3$	1	LeakyReLU
Conv	$32 \times 32 \times 32$	32	$3 \times 3$	2	LeakyReLU
DropOut (0.2)	$16 \times 16 \times 32$	-	-	-	-
Conv	$16 \times 16 \times 32$	64	$3 \times 3$	1	LeakyReLU
Conv	$16 \times 16 \times 64$	64	$3 \times 3$	2	LeakyReLU
DropOut (0.2)	$8 \times 8 \times 64$	-	-	-	-
Conv	$8 \times 8 \times 64$	128	$3 \times 3$	1	LeakyReLU
Conv	$8 \times 8 \times 128$	128	$3 \times 3$	2	LeakyReLU
DropOut (0.2)	$4 \times 4 \times 128$	-	-	-	-
Conv	$4 \times 4 \times 128$	256	$3 \times 3$	1	LeakyReLU
Flatten	$4 \times 4 \times 256$	-	-	-	-
Dense	128	-	-	-	-
DropOut (0.4)	128	-	-	-	-
Dense	3	-	-	-	Softmax
Total parameters	1 107 882				

# GAN model: Generator configuration

Generator					
Layer	Input	Channels	<i>Kernel size</i>	<i>Stride</i>	Activation
Latent	100	-	-	-	-
Dense	4096	-	-	-	LeakyReLU
Re-shape	$4 \times 4 \times 256$	-	-	-	-
Deconv	$4 \times 4 \times 256$	256	$4 \times 4$	2	LeakyReLU
Deconv	$8 \times 8 \times 256$	128	$4 \times 4$	2	LeakyReLU
Deconv	$16 \times 16 \times 128$	64	$4 \times 4$	2	LeakyReLU
Conv	$32 \times 32 \times 64$	3	$3 \times 3$	1	Tanh
Total parameters	2 119 811				

# Models parameters and hyperparameters

Summary of model parameters							
Name	Model hyperparameters					Data	
Method	Input	Batch	Opt	LR	Ep/It	CV	Geo. level
TL_VGG	4096	-	lbfgs	-	1000	5	Global/City
TL_VGG_GAP	512	-	lbfgs	-	1000	5	Global//city
FT_VGG	$224 \times 224 \times 3$	128	Adam	$1e^{-3}$	100	5	Global/City
FT_VGG_GAP	$224 \times 224 \times 3$	128	Adam	$1e^{-3}$	100	5	Global/City
SSL_GAN_Dis	$32 \times 32 \times 3$	128	Adam	$1e^{-3}$	100	5	Global
SSL_GAN_Gen	100	128	Adam	$1e^{-3}$	100	5	Global

\* Parameters were found using GridSearchCV.

# **Experiments & Results**

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# Environment

- We divide data to **80%** to train set and **20%** to test set.
- Trained on GPU NVIDIA GeForce GTX 1070, 8 Gb VRAM.
- We use a **StratifiedKFold** to avoid classes disproportion.
- We perform 5 cross-validation for each experiment over the train set using **25%** to validation set.
- We use EarlyStop in 30 epochs and DecayLR every 8 epochs.

# Metrics

- **Accuracy** — *What percent of the data were predicted correct?*
- **Precision** — *What percent of your predictions were correct?*
- **Recall** — *What percent of the positive cases did you catch?*
- **F1 score** — *What percent of positive predictions were correct?*

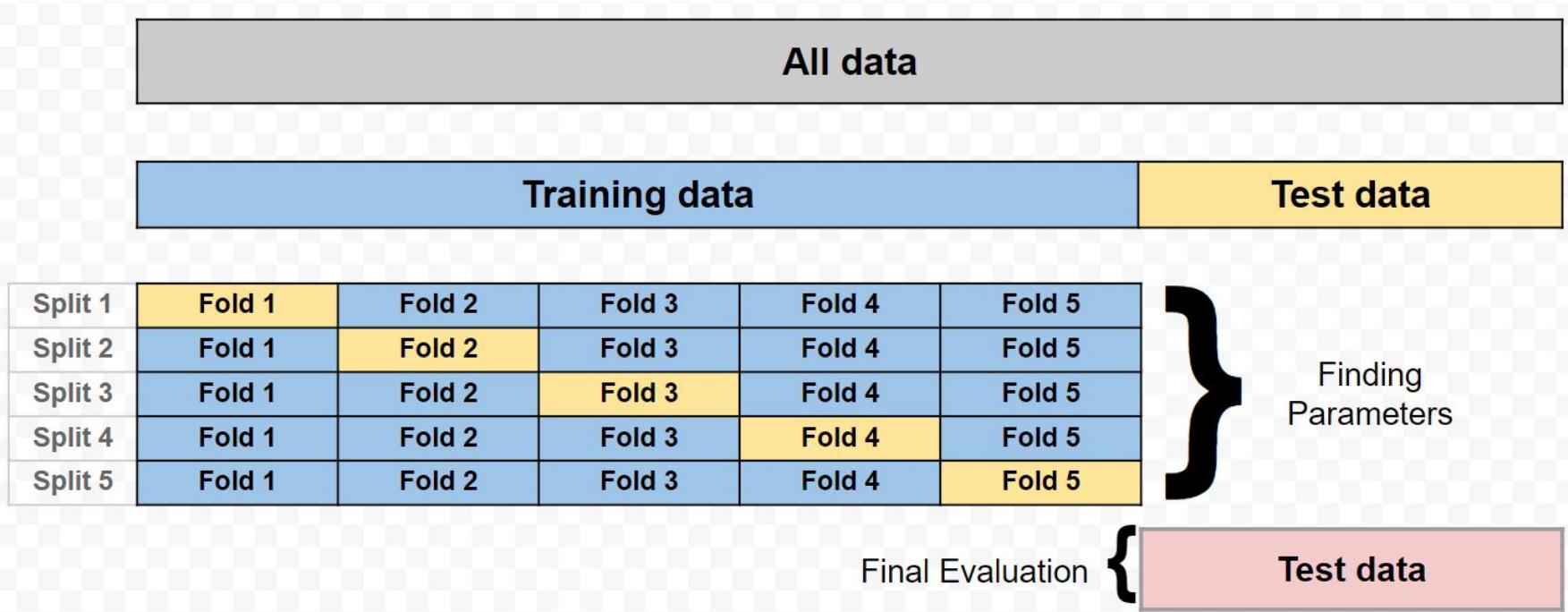
$$\text{Accuracy} = \frac{T_P + T_N}{T_P + T_N + F_P + F_N}$$

$$\text{Precision} = \frac{T_P}{T_P + F_P}$$

$$\text{Recall} = \frac{T_P}{T_P + F_N}$$

$$F1_{score} = 2 \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

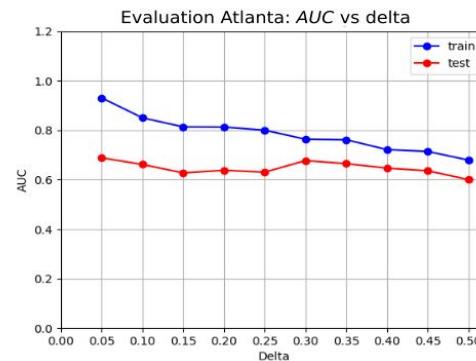
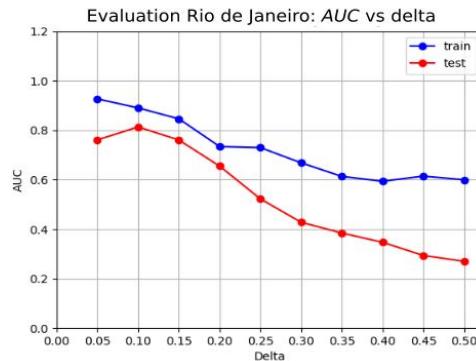
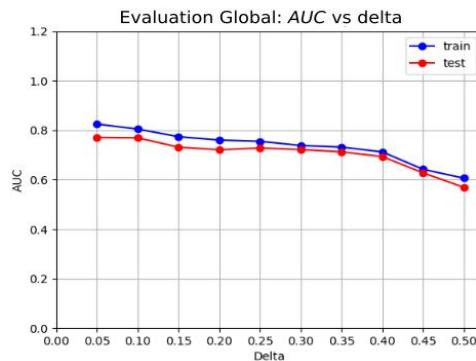
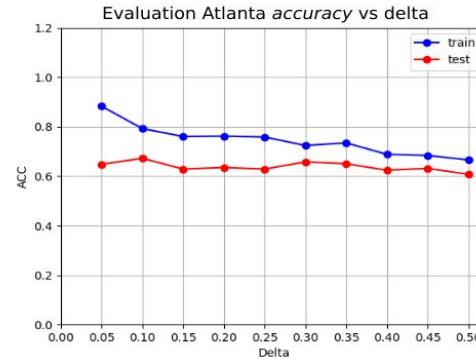
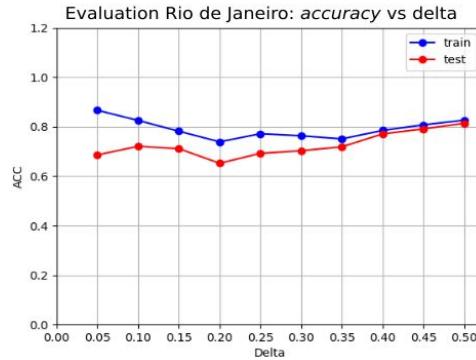
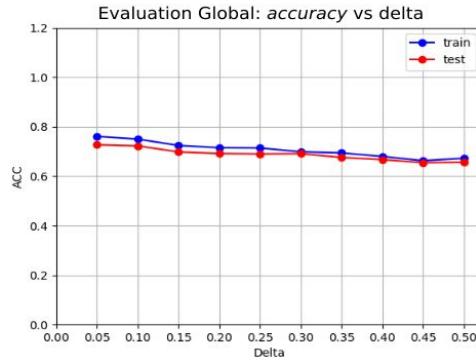
# Data Split: K-fold cross validation



\* We use 20% of the training set to validation set.

\* All results presented are corresponding to test data

# Transfer-Learning models results



\* Results of testing using different values of  $\delta$ .

# Transfer-Learning models results

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

\* Results of testing using all dataset.

# Transfer-Learning models results

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

\* Results of testing using all dataset.

# Transfer-Learning models results

Model	Method	auc		accuracy		f1 score	
		train	eval	train	eval	entrena	eval
ResNet50	<i>Linear SVC</i>	61.62	59.10	68.10	<b>66.42</b>	53.63	50.80
	<i>Logistic</i>	60.04	<b>59.15</b>	67.25	66.37	51.47	49.70
	<i>Ridge Classifier</i>	62.11	58.38	68.36	66.08	54.59	<b>51.00</b>
	<i>RBF SVC</i>	45.36	44.07	53.46	53.57	44.99	44.98
Xception	<i>LinearSVC</i>	55.29	<b>53.25</b>	64.43	<b>63.33</b>	41.66	39.69
	<i>Logistic Regression</i>	53.48	52.75	63.56	63.14	36.72	35.87
	<i>Ridge Classifier</i>	57.23	52.22	65.22	63.04	45.63	42.11
	<i>RBF SVC</i>	45.575	44.99	49.12	49.12	55.01	<b>55.05</b>

\* Results of testing using all dataset.

# Fine-Tuned models results

Models “FT”	<i>auc</i>		<i>accuracy</i>		<i>f1 score</i>	
	train	eval	train	eval	train	eval
<i>VGG</i>	77.83	<b>77.42</b>	74.01	64.71	74.01	64.69
<i>VGG_GAP</i>	76.145	75.59	69.40	66.88	69.41	66.87
<i>VGG_Places</i>	77.98	77.35	70.52	<b>67.28</b>	70.52	<b>67.28</b>
<i>VGG_GAP_Places</i>	74.95	74.75	68.71	67.26	68.71	67.27
<i>ResNet50</i>	76.362	72.71	70.36	65.64	67.35	64.98

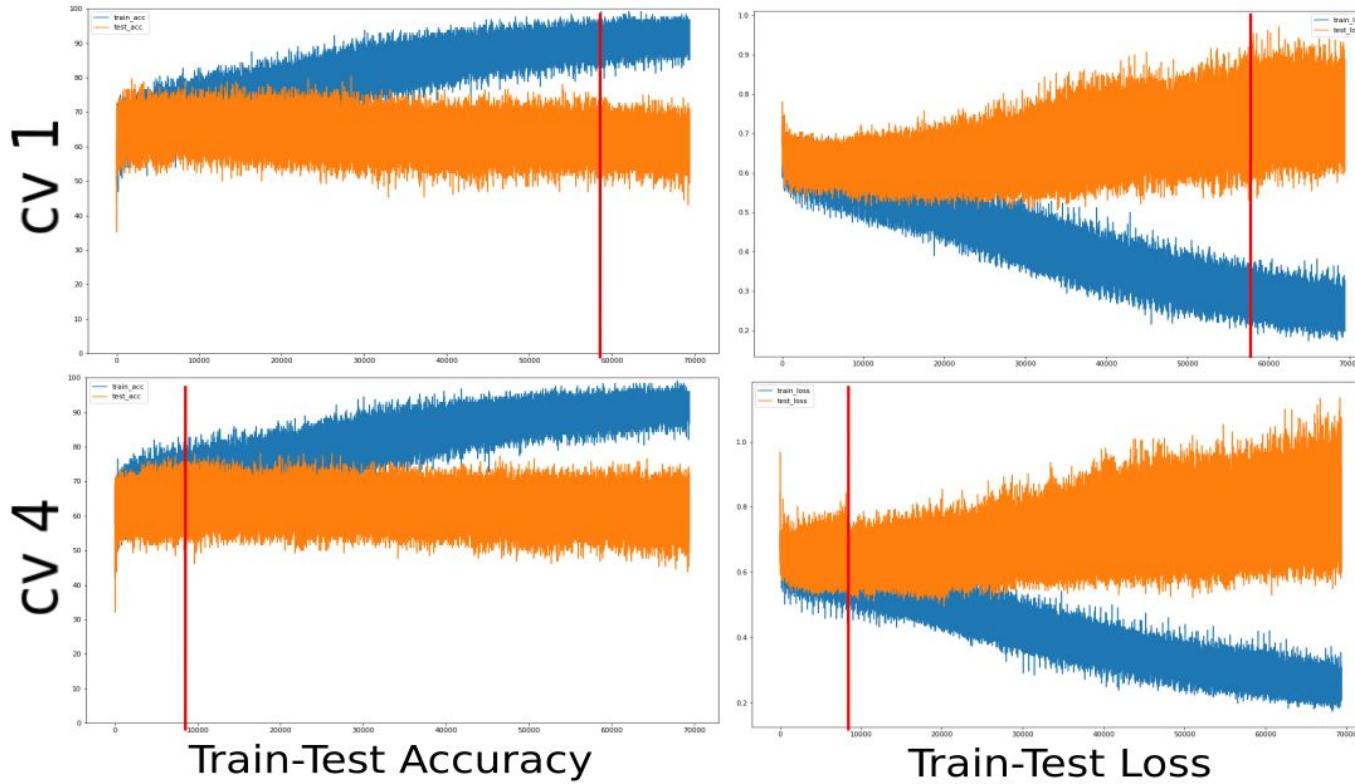
\* Results of testing using all dataset.

# GAN model results

Model 32x32x3	CV	<i>auc</i>		<i>accuracy</i>		<i>f1 score</i>	
		train	eval	train	eval	train	eval
SSL_GAN	0	80.95	80.97	90.26	59.06	90.26	59.04
	1	81.43	81.45	89.42	61.50	89.42	61.48
	2	81.43	<b>81.45</b>	89.56	<b>62.58</b>	89.56	<b>62.57</b>
	3	80.59	80.66	90.01	61.52	90.01	61.54
	4	80.61	80.63	89.38	61.14	89.38	61.13

\* Results of testing using all dataset.

# GAN model results



# GAN model results

Model 32x32x3	CV	iteration	<i>auc</i>		<i>accuracy</i>		<i>f1 score</i>	
			train	eval	train	eval	train	eval
SSL-GAN	0	23788	73.89	73.89	78.90	78.12	78.90	78.12
	1	58550	80.21	<b>80.22</b>	92.18	<b>81.25</b>	92.18	<b>81.25</b>
	2	21951	73.60	73.60	81.25	79.68	81.25	79.68
	3	23180	73.53	73.53	76.56	78.90	76.56	78.90
	4	8602	69.84	69.84	74.21	78.90	74.21	78.90

\* Results of testing using all dataset.

# GAN model results



# Simple Landscape to show results



# Training time

Training time for each model		
Method	Data	Average Time
SSL_GAN	Global	1 and a half week
FT_VGG	Global	8 hours
FT_VGG	56 Cities	6 hours
FT_VGG_GAP	Global	7 hours
FT_VGG_GAP	56 Cities	5 hours
TL_VGG	Global	15 minutes
TL_VGG	56 Cities	10 minutes
TL_VGG_GAP	Global	9 minutes
TL_VGG_GAP	56 Cities	6 minutes

\* Training time using the environment described above.

# Conclusions

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# Main Contributions

- We propose a methodology to analyze the Place Pulse 2.0 dataset since we thought that is better to focus on data first instead of model complexity.
- We show Place Pulse dataset limitations, some of them based on how the dataset was built and others based on the pre-processing.
- We show that in order to get a better performance in how to differentiate safe characteristics, a semi-supervised model fits the necessity of training this complex dataset with the limitations explained before.
- We solved the problem of imbalance, individual city identification, and lack of samples per city using a semi-supervised GAN model. In other words, we can fix 3 dataset limitations in Place Pulse.

# Publications

- Felipe Moreno-Vera, Bahram Lavi, and Jorge Poco. “**Quantifying Urban Safety Perception on Street View Images**”. In IEEE/WIC/ACM International Conference on Web Intelligence (WI-IAT ’21), December 14–17, 2021, Essendon, Australia.
- Felipe Moreno-Vera, Bahram Lavi, and Jorge Poco. “**Urban Perception: Can We Understand Why a Street Is Safe?**”. In Mexican International Conference on Artificial Intelligence (MICAI ’21), October 25-30, 2021, Mexico City, Mexico.
- Felipe Moreno-Vera. “**Understanding Safety based on Urban Perception**”. In International Conference on Intelligent Computing (ICIC ’21), August 12-15, 2021, Shenzhen, China.

# Questions?