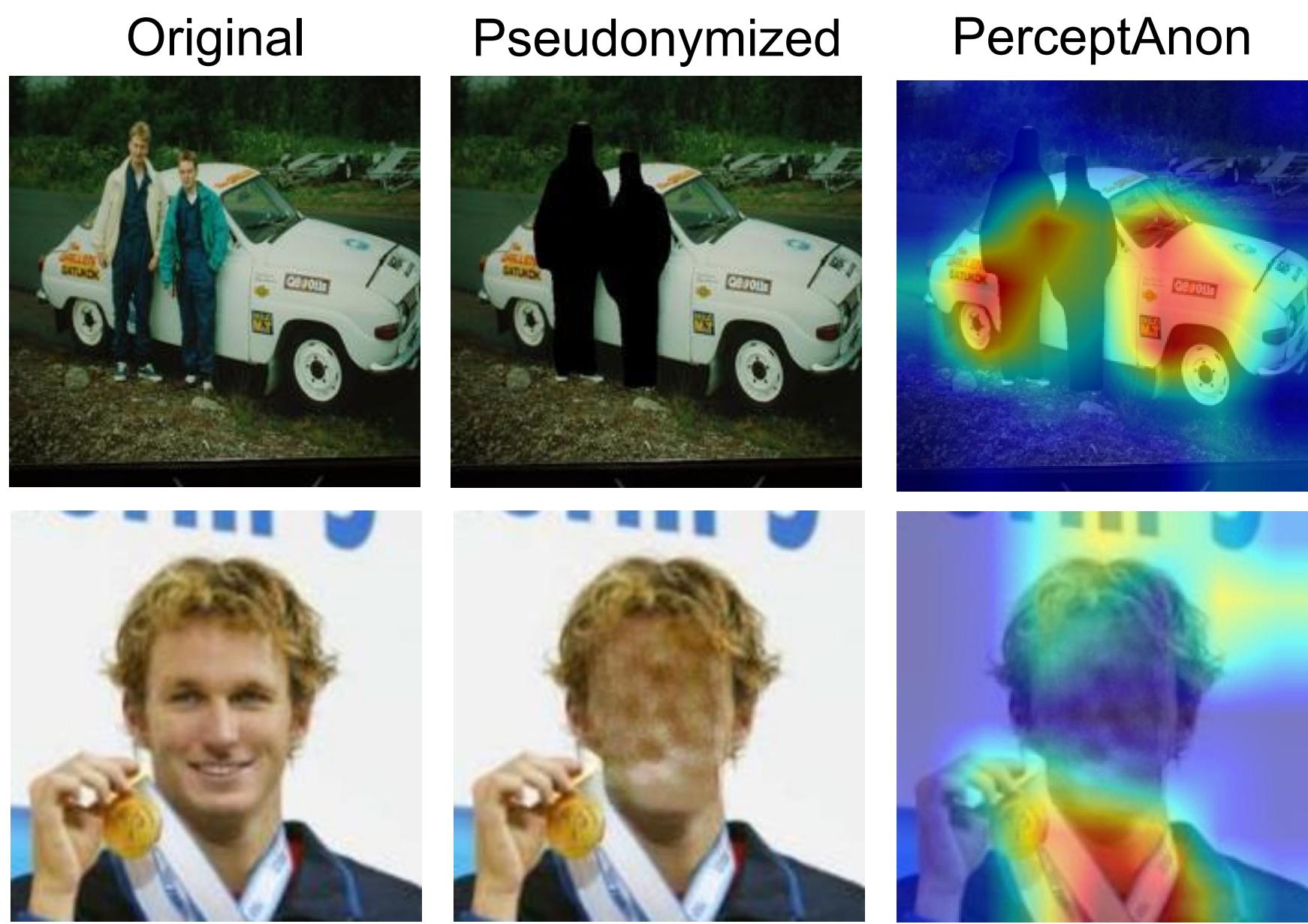


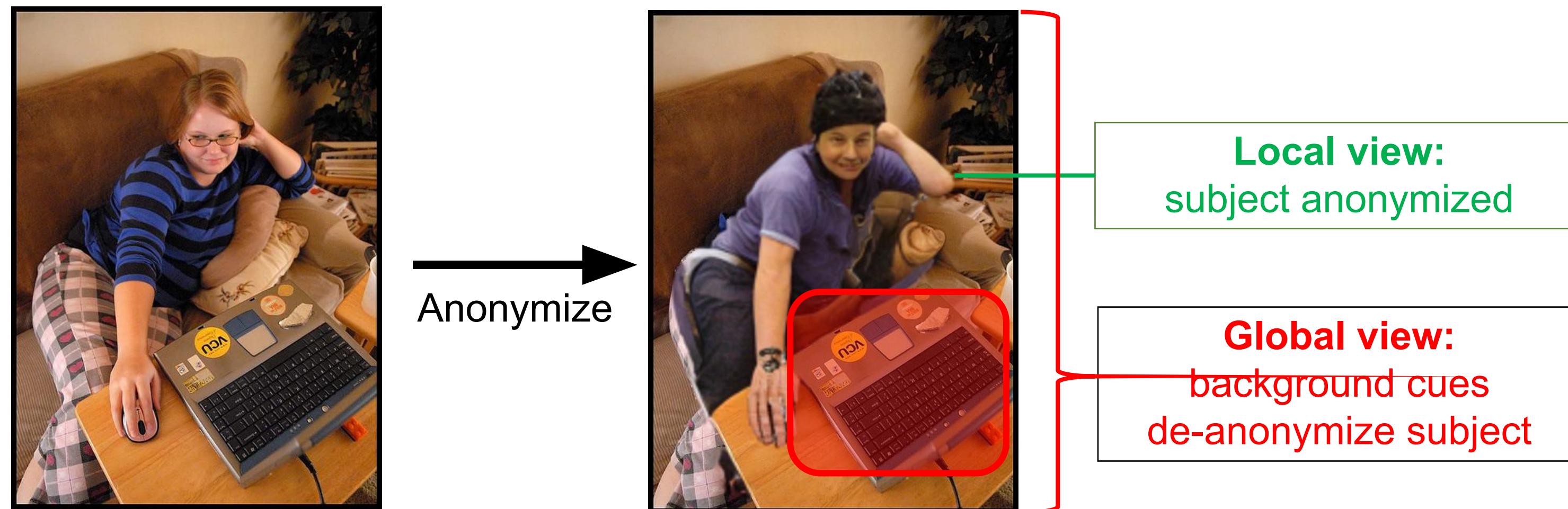
## Task Definition

- General Data Protection Regulation (GDPR): "the use of additional information can lead to identification of individuals"
- PerceptAnon (**Perception of Anonymization**) identifies and quantifies privacy-compromising cues in face/full body pseudonymized images.



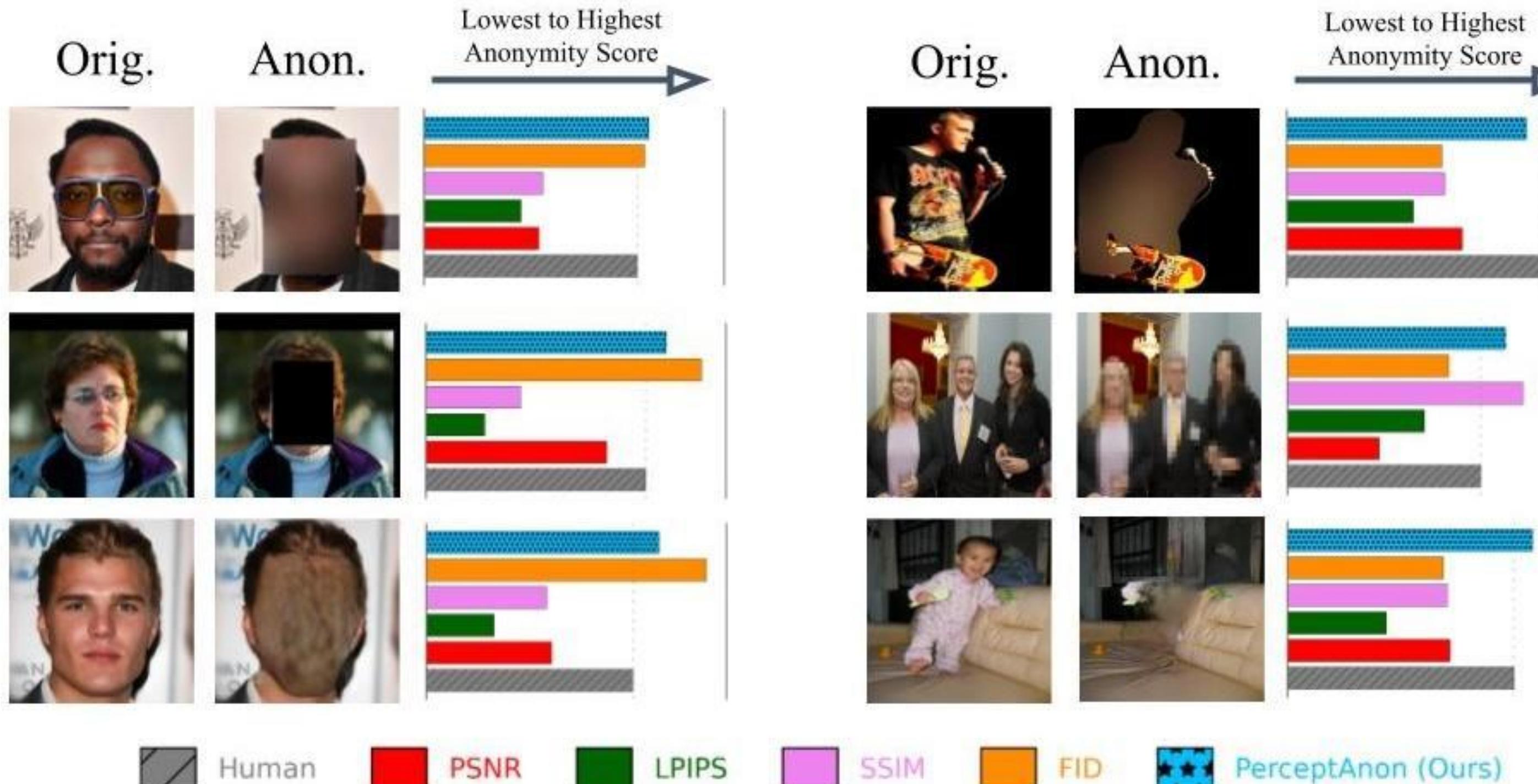
## Motivation

Are images fully anonymized according to humans?



- Current anonymization techniques focus on **local** face/full body **pseudonymization**.
- This can leave privacy compromising background cues **globally**.
- Humans interpret images holistically to identify and assess such cues.

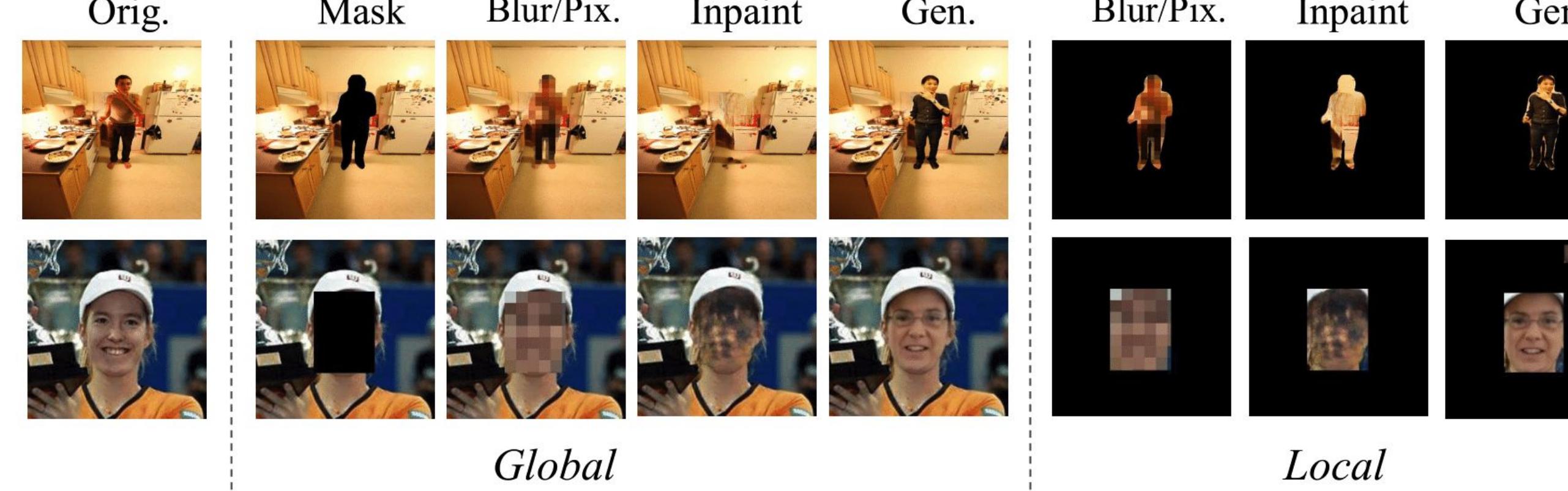
## Existing global image metrics and their alignment with human perception



- Existing metrics do not correlate well with human perception.

## Proposed metric

### New dataset for face/full-body anonymity

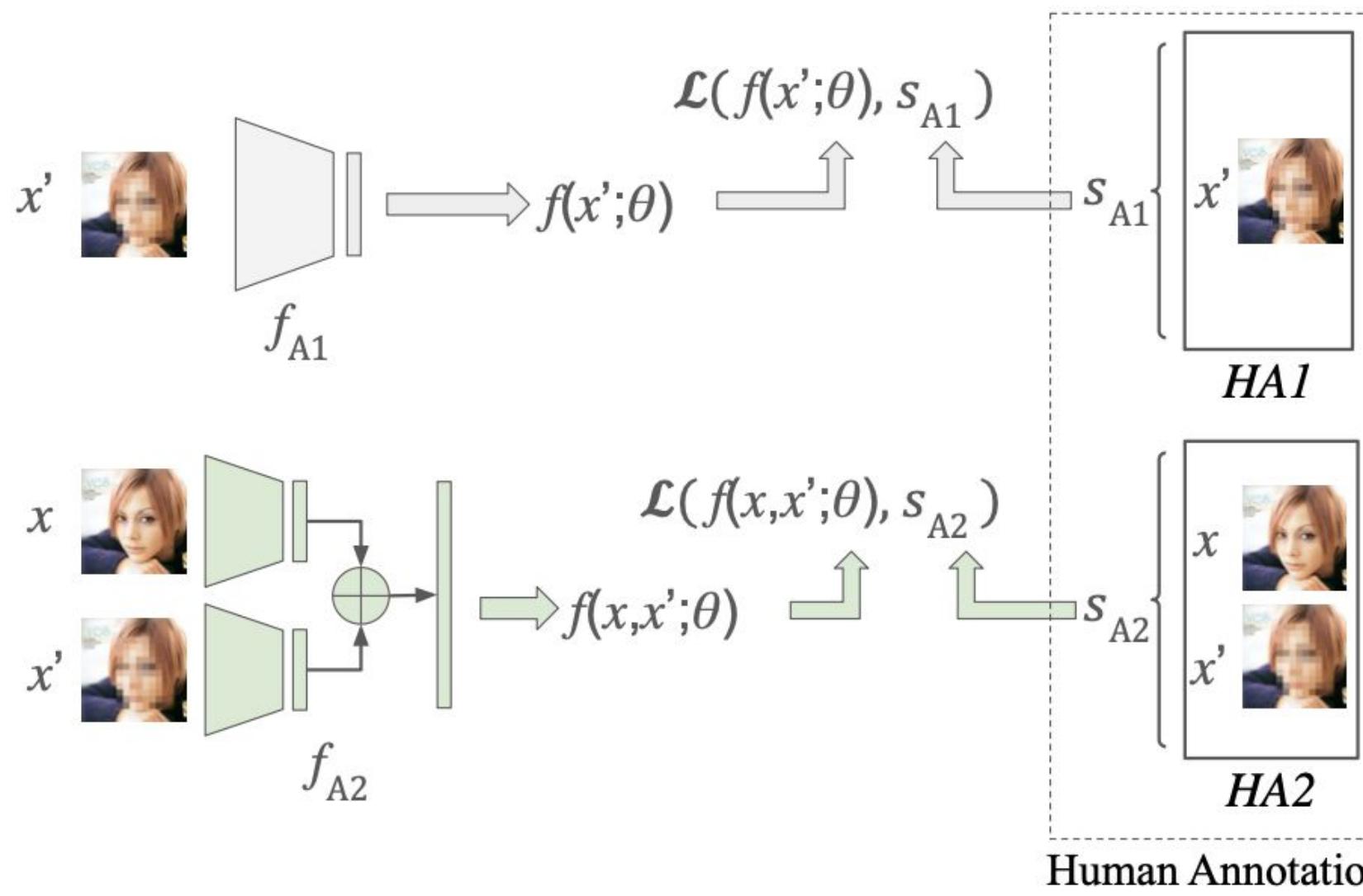


Annotations score 1-10 on degree of anonymity achieved. Two human annotation setups:

- HA1: annotators only see anonymized image
- HA2: annotators original and anonymized image pairs

### PerceptAnon metric

- HA1: CNN with anonymized image input ( $x'$ )
- HA2: Siamese network with original-anonymized image pair input ( $x, x'$ )



Trained using both classification (CE) and regression (MSE) loss

## Main Results

### Comparison of different metrics on our dataset train/test splits

#### HA1

Train/Test Setup	Metrics	PSNR	MSE	LPIPS	SSIM	FID	PerceptAnon (Ours)
All	$\rho$	-0.7011	0.7011	0.7675	-0.8358	0.6578	<b>0.8817</b>
	$\tau$	-0.5018	0.5018	0.5544	<b>-0.7601</b>	0.4667	0.7119
LOOV-VOC	$\rho$	-0.7448	0.7448	0.8244	-0.8185	0.6995	<b>0.8603</b>
	$\tau$	-0.5437	0.5437	0.6288	-0.6289	0.5095	<b>0.6570</b>
LOOV-COCO	$\rho$	-0.771	0.771	0.805	-0.7702	0.733	<b>0.8643</b>
	$\tau$	-0.5649	0.5649	0.6051	-0.5712	0.5385	<b>0.6845</b>
LOOV-LFW	$\rho$	-0.7354	0.7354	0.7574	-0.7615	0.7289	<b>0.8278</b>
	$\tau$	-0.5256	0.5256	0.5487	-0.5509	0.5141	<b>0.6353</b>
LOOV-CelebA	$\rho$	-0.6239	0.6239	0.7301	-0.7321	0.6634	<b>0.8478</b>
	$\tau$	-0.4407	0.4407	0.5151	-0.518	0.4594	<b>0.6549</b>
Task-Person	$\rho$	-0.7313	0.7313	0.7909	-0.75	0.6858	<b>0.8831</b>
	$\tau$	-0.524	0.524	0.5929	-0.5452	0.4971	<b>0.7120</b>
Task-Face	$\rho$	-0.7547	0.7547	0.7906	-0.7838	0.7447	<b>0.8774</b>
	$\tau$	-0.5528	0.5528	0.5887	-0.5825	0.547	<b>0.6940</b>

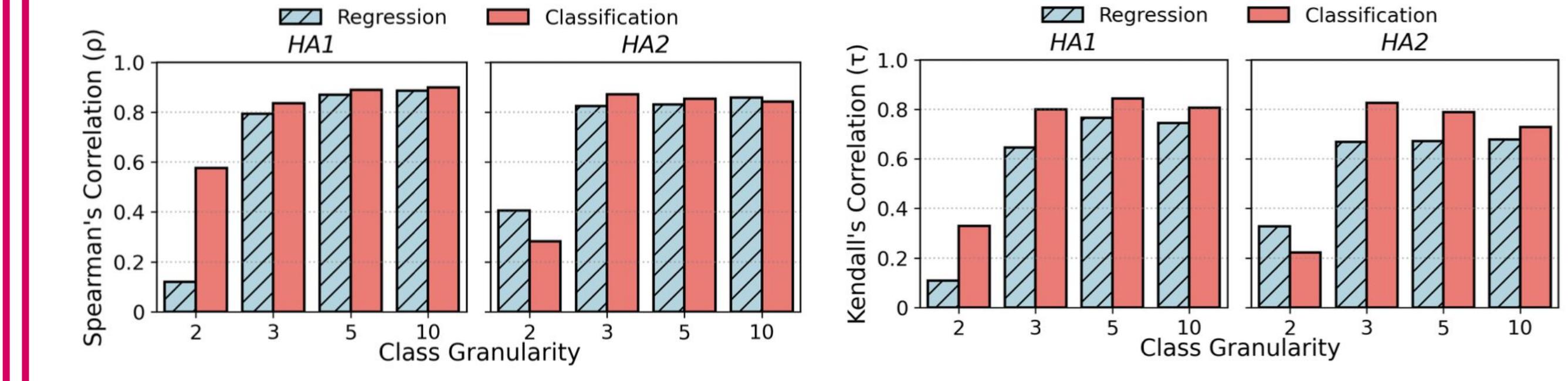
#### HA2

Train/Test Setup	Metrics	PSNR	MSE	LPIPS	SSIM	FID	PerceptAnon (Ours)
All	$\rho$	-0.7631	0.7631	0.7622	-0.7655	0.6444	<b>0.8421</b>
	$\tau$	-0.5434	0.5434	0.5385	-0.5448	0.4456	<b>0.6477</b>
LOOV-VOC	$\rho$	-0.7833	0.7833	0.7869	-0.7971	0.6203	<b>0.8218</b>
	$\tau$	-0.575	0.575	0.5694	-0.5827	0.4338	<b>0.6211</b>
LOOV-COCO	$\rho$	-0.7941	0.7941	0.7851	-0.785	0.6478	<b>0.8404</b>
	$\tau$	-0.5842	0.5842	0.5713	-0.5739	0.4559	<b>0.6456</b>
LOOV-LFW	$\rho$	-0.7551	0.7551	0.7137	-0.7358	0.7032	<b>0.8462</b>
	$\tau$	-0.5243	0.5243	0.4683	-0.5001	0.4536	<b>0.6495</b>
LOOV-CelebA	$\rho$	-0.7157	0.7157	0.7082	-0.7542	0.679	<b>0.8250</b>
	$\tau$	-0.4875	0.4875	0.4753	-0.5354	0.4569	<b>0.6270</b>
Task-Person	$\rho$	-0.7757	0.7757	0.7833	-0.7997	0.6408	<b>0.8320</b>
	$\tau$	-0.5647	0.5647	0.5668	-0.5872	0.4477	<b>0.6328</b>
Task-Face	$\rho$	-0.7435	0.7435	0.6956	-0.7623	0.6756	<b>0.8590</b>
	$\tau$	-0.5154	0.5154	0.4537	-0.5387	0.4454	<b>0.6675</b>

- PerceptAnon has stronger correlation to human perception than existing metrics.

## Analysis of PerceptAnon

### How to best align PerceptAnon with respect to human perception?



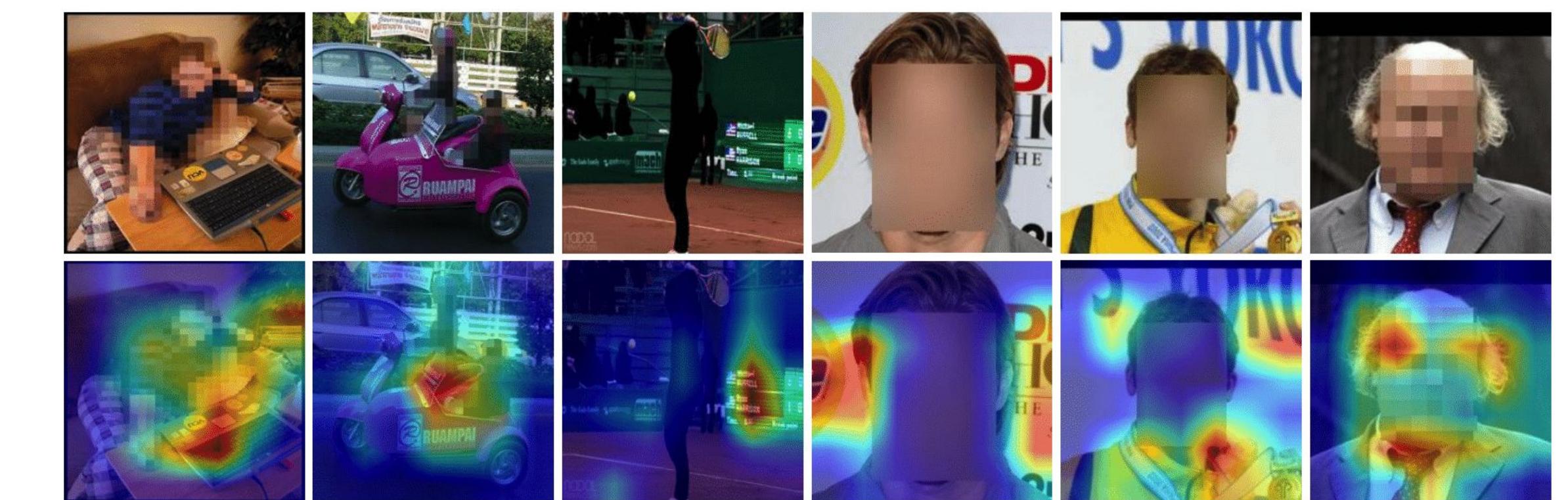
PerceptAnon's faithfulness to human perception under:

- Varying class granularities
- Regression vs. classification training strategy

### Correlation between HA1 and HA2

Model	HA1	HA2	$\rho(HA1, HA2)$
ResNet18	0.8752	0.8345	0.9050
ResNet50	0.8912	0.8346	0.8848

### PerceptAnon GRAD-CAM visualizations



- PerceptAnon focuses on remaining potential privacy compromising cues

## Future work

- Extend PerceptAnon to consider different characteristics like medical images.
- Develop anonymization techniques that consider full anonymity including residual privacy compromising cues in anonymized image background.

## Conclusion

- Image anonymity often equates to pseudonymity; no current metric addresses global image privacy, including residual background cues.
- We propose novel annotation and evaluation setups to study and understand image privacy from a human perspective.
- We introduce **PerceptAnon**, a learning-based metric that better aligns with human perception of global image privacy.
- PerceptAnon not only considers original-anonymized image pairs but also sole anonymized images, mimicking human perception.

### Contact:

- kpatwari@ucdavis.edu
- viveksharma@sony.com

### Reference:

10 Misunderstanding Related To Anonymisation, European Union, EDPS. 2021



### Project

### Github