

Curse and bless of bias

Identifying, mitigating and inducing it in CV

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Contents

Towards computer vision in real scenarios: robustness to unexpected variations

A “bias(ed) perspective” on model robustness

Identifying/Understanding bias: shortcut learning in the Fourier domain

Mitigating bias: augmentations, and (demographic) privacy-preserving face analysis

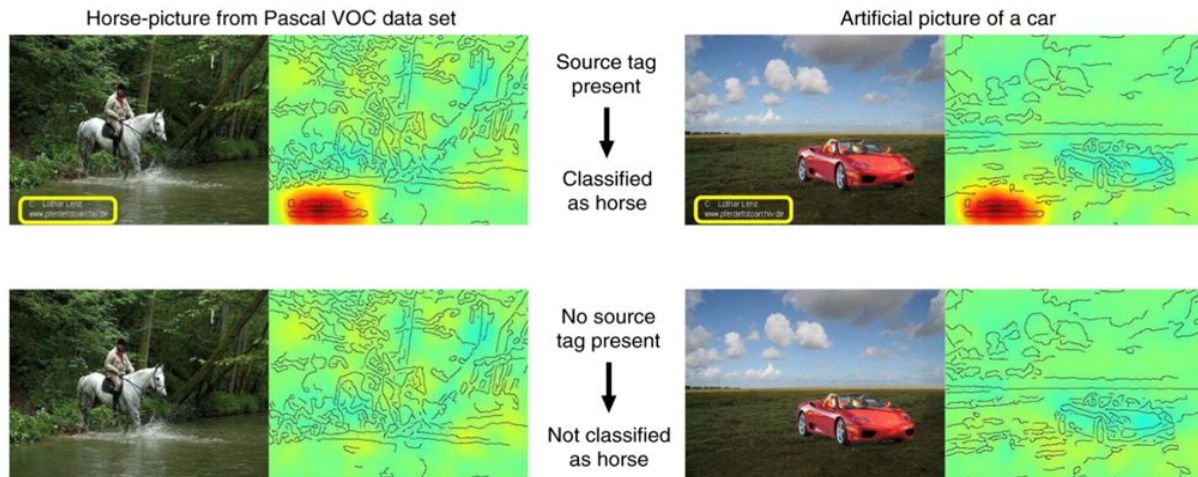
Inducing (positive) bias

Expert knowledge from neurophysiology findings

Camera pose priors in visual place recognition

Identifying bias: Simplicity Bias and Shortcut Learning

Networks tend to **learn easy (less costly) solutions** to a problem [1]



Lapuschkin, S. *et al.* **Unmasking Clever Hans predictors and assessing what machines really learn.** *Nat Commun* **10**, 1096 (2019).

Shortcuts are decision rules based on *spurious correlations between data and ground truth*, rather than on the correlation of semantic and task-related cues [2]

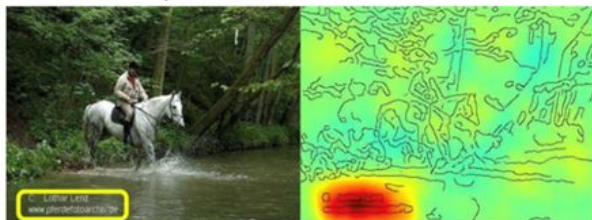
[1] Shah, H., *et al.* (2020). **The Pitfalls of Simplicity Bias in Neural Networks.** In NeurIPS 2020 (pp. 9573–9585).

[2] Geirhos, R., *et al.* (2020). **Shortcut learning in deep neural networks.** *Nature Machine Intelligence*, 2(11), 665–673.

Frequency (implicit) shortcuts

these can be computed - we designed an algorithm for 'culling irrelevant frequencies'

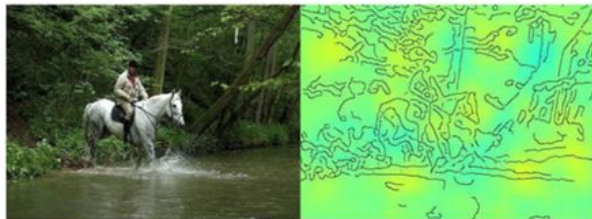
Horse-picture from Pascal VOC data set



Source tag present



Classified as horse



No source tag present

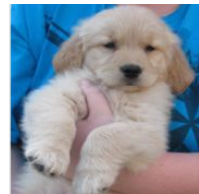


Not classified as horse

explicit, visible shortcuts



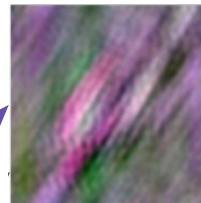
true class: **frog**
predicted: **frog**



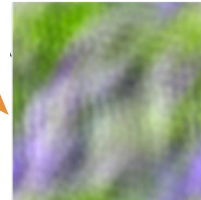
true class: **golden retriever**
predicted: **golden retriever**



select only 'white' frequency components



predicted: **frog**

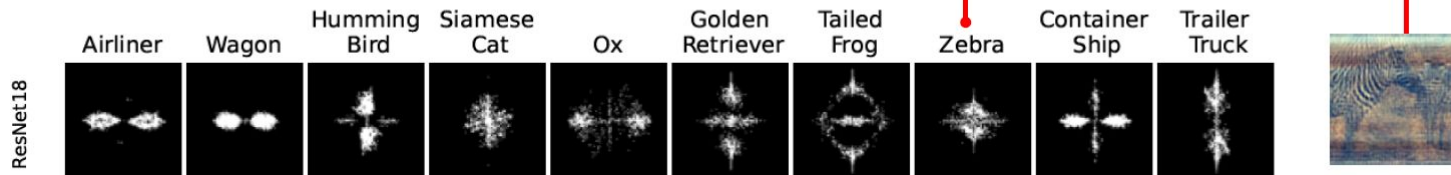


predicted: **frog**

implicit, difficulty to 'see', frequency shortcuts

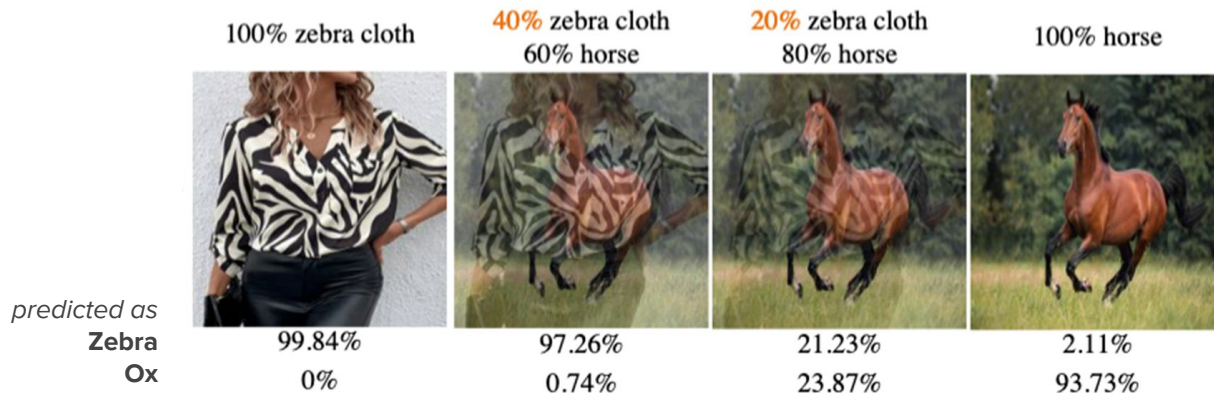
Frequency shortcuts and texture-bias of CNNs

affected by a frequency shortcut: a small set of frequency (texture) biases predictions

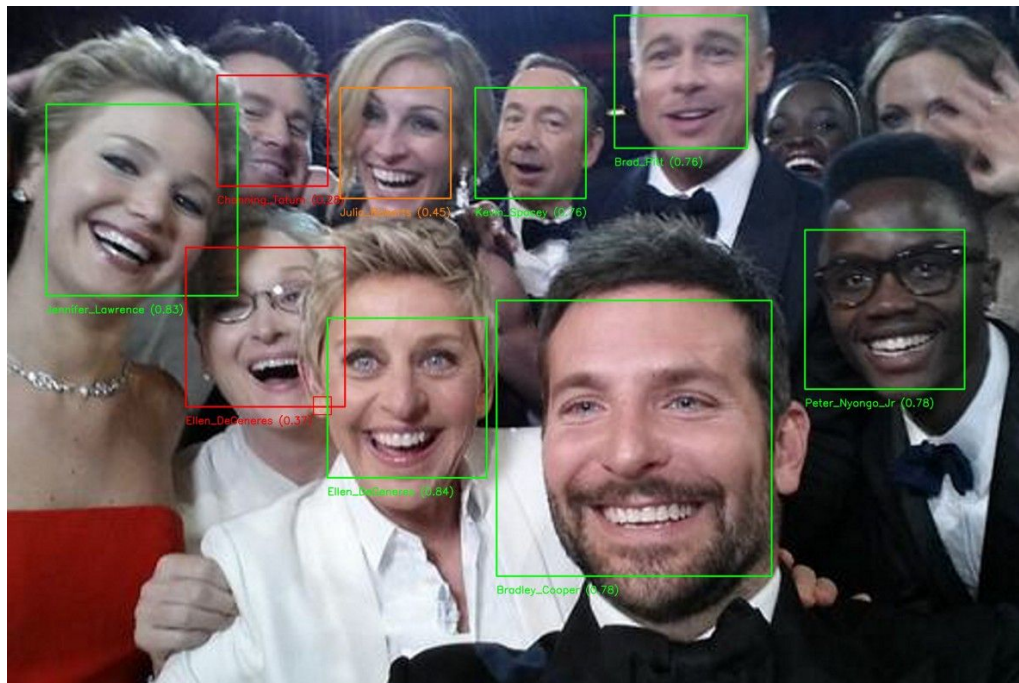


CNNs (trained on ImageNet) are texture-biased (Geirhos et al, ICLR 2019): we can measure this bias

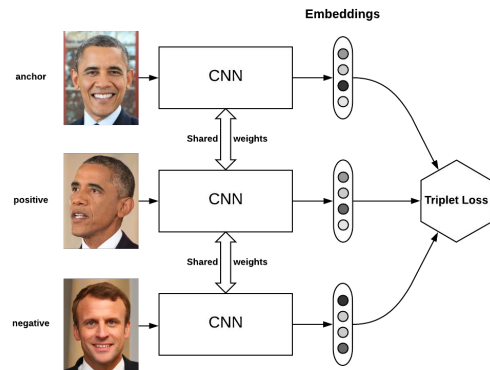
negative effects on generalization: not learning semantics



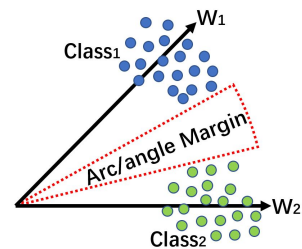
Mitigating bias in face analysis



FaceNet: minimize a triplet loss - push positive together and negative away

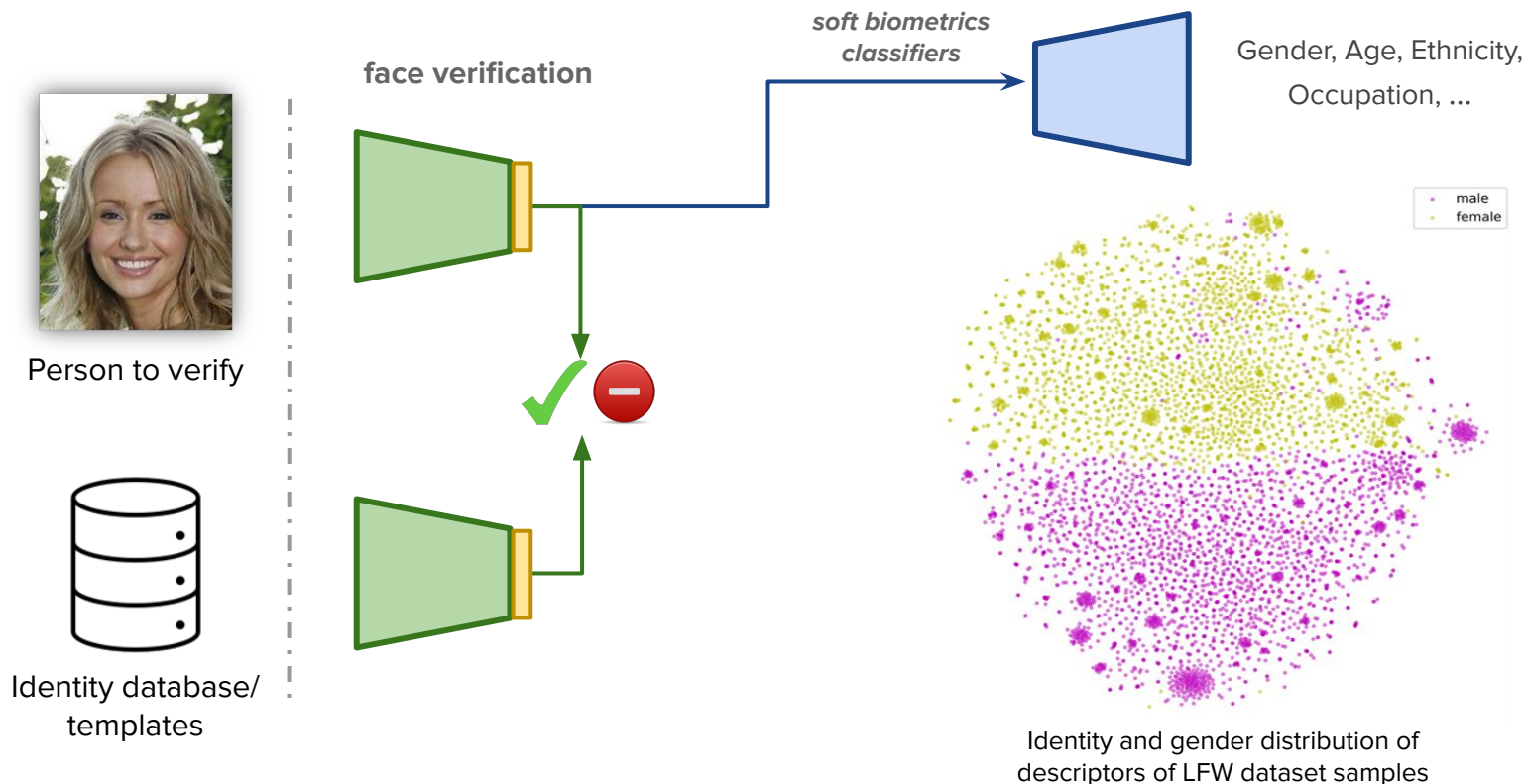


ArcLoss: faces of the same identity (classes) clustered together with high inter-class margin

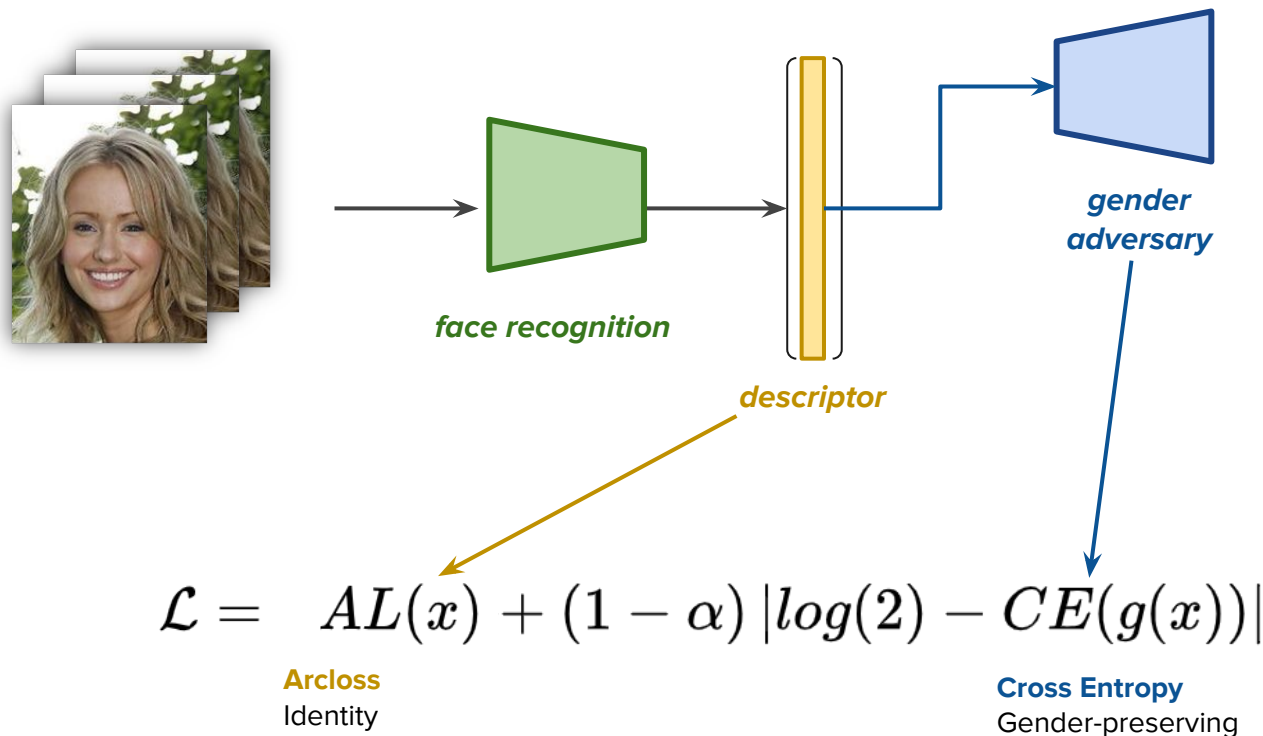


Problem!? Soft-biometrics are encoded in face recognition

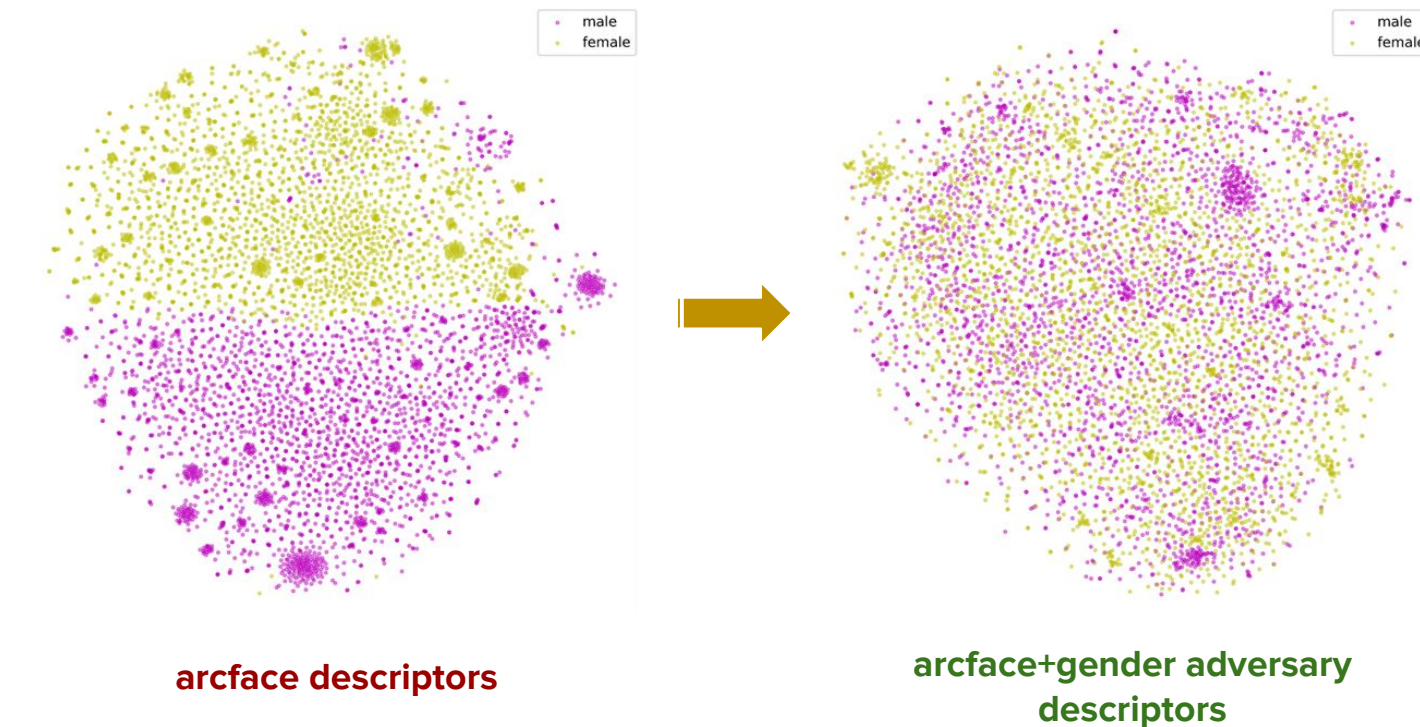
Un-bias the model from using soft biometrics => reduce (or trade-off) recognition by gender



Reduce bias by a gender-privacy adversary



Results: improved gender-privacy



Visual place recognition

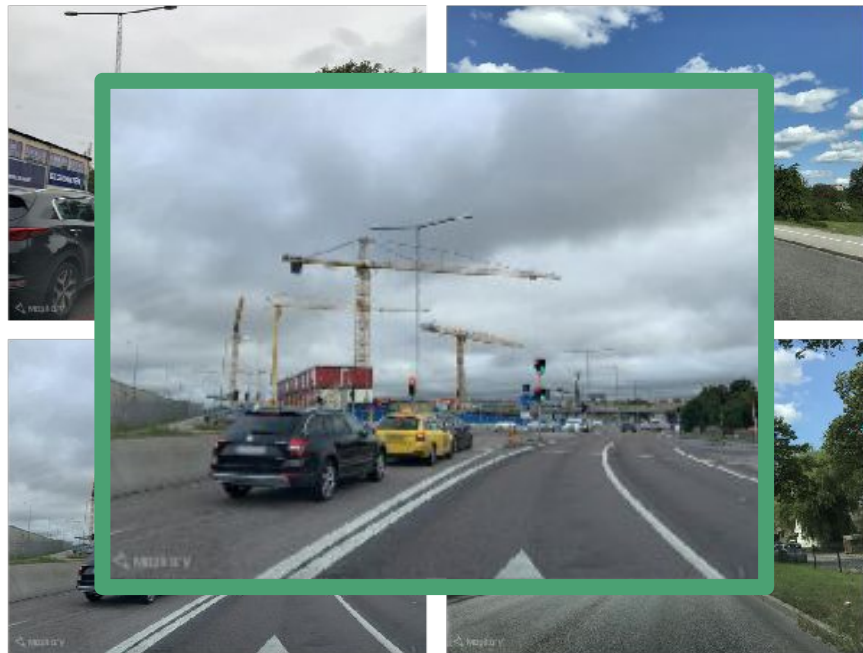
Inductive bias via application-related priors

Objective:

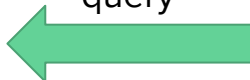
recognize whether two images depict the same place, under seasonal and weather changes, time-of-the-day variations, etc.



Visual place recognition: **an Image Retrieval task**



query



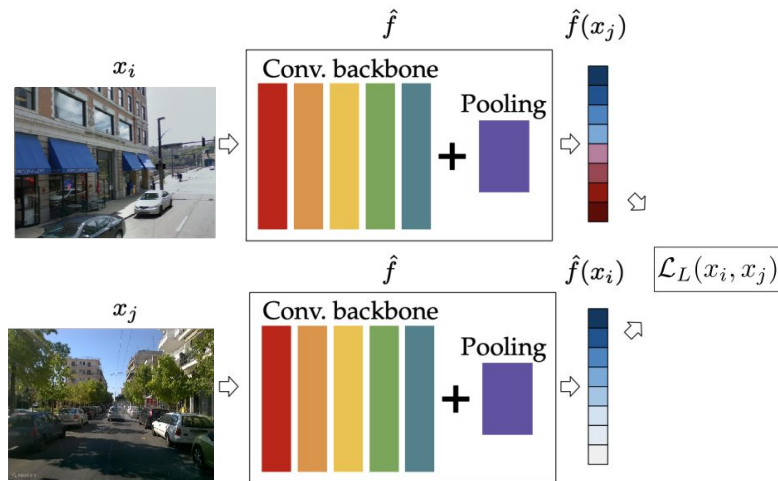
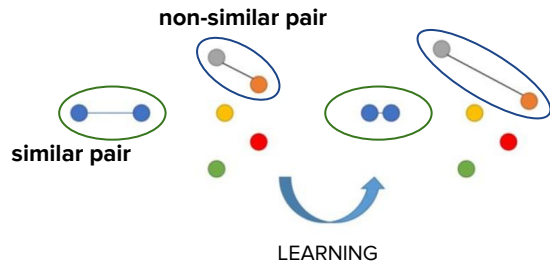
Contrastive learning of image descriptors

How

Train using image pairs (or triplets)

Objective

- Embed descriptor of **similar** images close together in a latent space
- ...descriptors of **non-similar** images are pushed away in a latent space



$$\mathcal{L}_{CL}(x_i, x_j) = \begin{cases} \frac{1}{2} d(\hat{f}(x_i), \hat{f}(x_j))^2, & \text{if } y_{i,j} = 1 \\ \frac{1}{2} \max(\tau - d(\hat{f}(x_i), \hat{f}(x_j)), 0)^2, & \text{if } y_{i,j} = 0 \end{cases}$$

Image similarity ground truth is *noisy*

Rule in VPR: images taken within 25 meters are of a similar place



28.6m away 

Image similarity as a *continuous* property

Similarity: ~~$y_{i,j} \in \{0, 1\}$~~ ~~binary similarity~~ needs to be reformulated $\longrightarrow \Psi_{i,j} \in [0, 1]$
 continuous similarity

+++

+

++



5.6 m



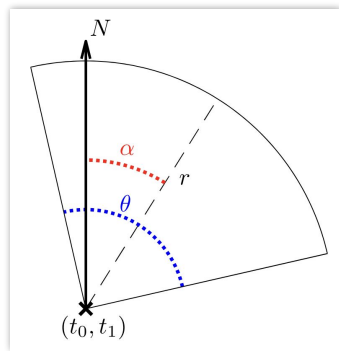
24.7 m



25.2 m

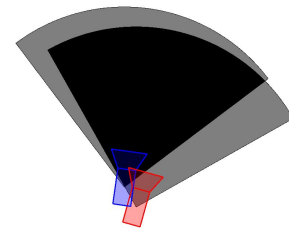
Similarity via camera/scene geometry priors

Estimate the Field-of-View of the camera, using extra information in the data sets



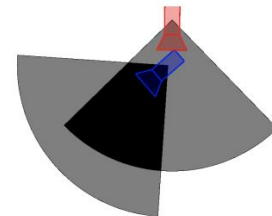
r : radius
 Θ : fov angle
 α : direction

Mapillary Street Level Sequences (MSLS): GPS + compass angle



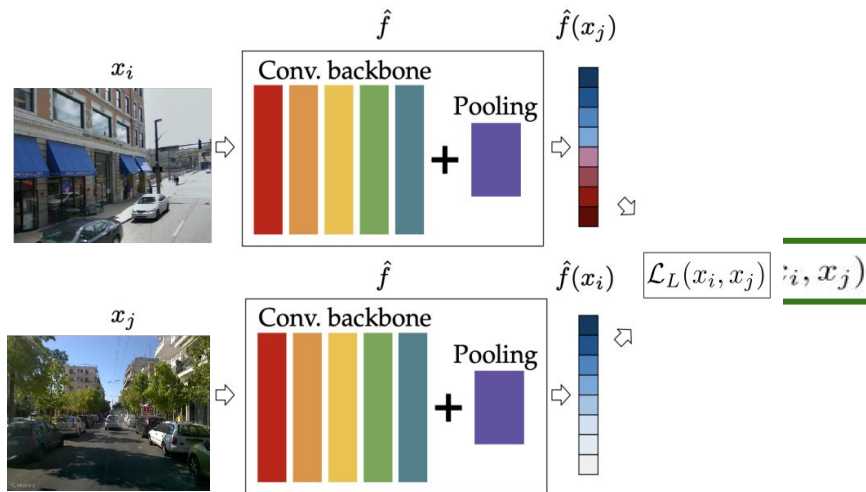
$$\Psi = 0.755$$

TrimBot2020 TB-Places: laser tracker + IMU (6dof camera pose)



$$\Psi = 0.41$$

Generalized Contrastive Loss: induce continuous (pose) similarity prior into Contrastive Learning

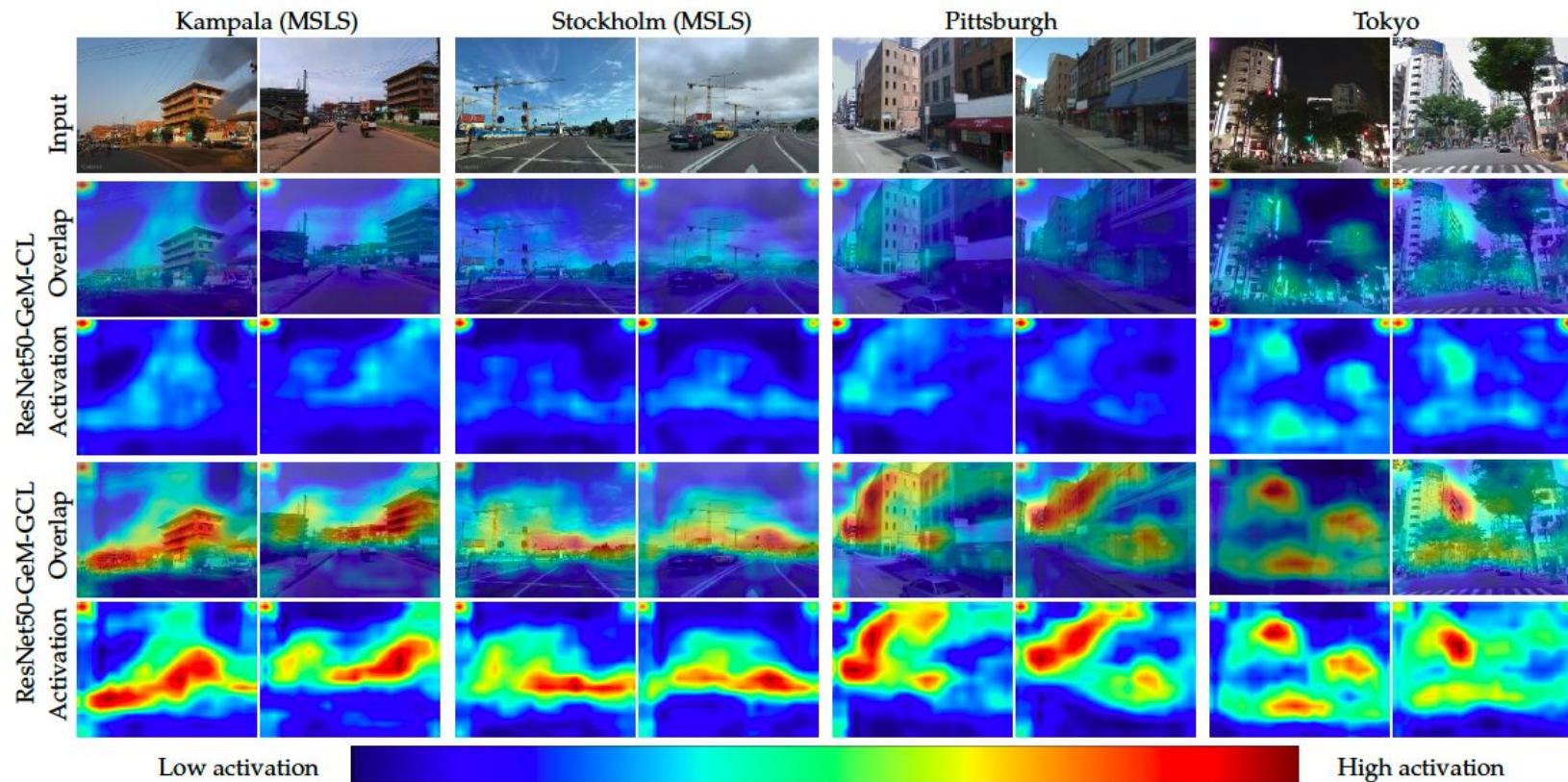


**Generalized
Contrastive Loss**

$$\mathcal{L}_{GCL}(x_i, x_j) = \mathcal{L}_{CL}(x_i, x_j) + \left(1 - \frac{1}{2} \max\left(\frac{d(\hat{f}(x_i), \hat{f}(x_j))}{\psi_{i,j}}, 0\right)\right) \frac{1}{2} d(\hat{f}(x_i), \hat{f}(x_j))^2$$

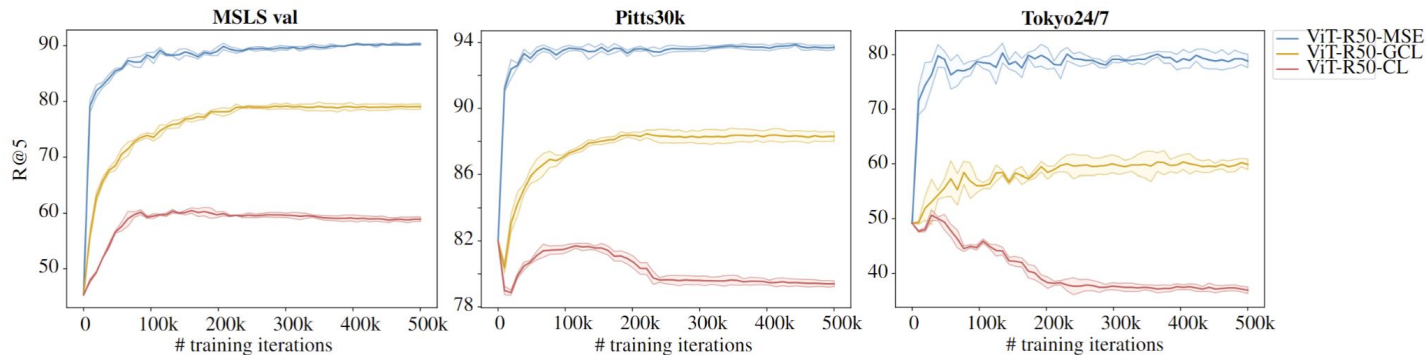
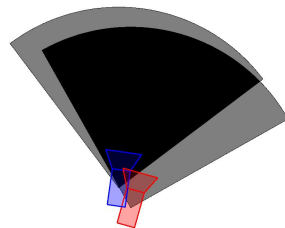
**continuous
similarity**

What the GCL looks at



What if? Learning VPR descriptors by regression

Descriptor distance as direct measure of fov overlap (image similarity)



data-efficiency and better performance

Summary and *take home* message

- Networks **may learn shortcuts** and/or biased descriptors (*bias in data*)
- **Prior knowledge** helps to robustify computer vision models
 - Visual system is robust to variations and generalizes well: use neurophysiology findings into CV model design (!)
 - Application-related priors (f.i. camera FoV overlap in VPR) also work
 - ... *any ideas for priors* ...

Curse and bless of bias

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Thank
You!

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