EUROGRAPHICS
CONFERENCE 2024

Predicting Perceived Gloss: Do Weak Labels Suffice?

Julia Guerrero-Viu*[1], J. Daniel Subias*[1], Ana Serrano[1], Katherine R. Storrs[2], Roland W. Fleming[3,4], Belen Masia[1], Diego Gutierrez[1]

[1]Universidad de Zaragoza, I3A [2]University of Auckland [3]Justus Liebig University Giessen
[4]Center for Mind, Brain and Behaviour, Universities of Marburg and Giessen

* Joint first authors

[NVIDIA MDL]


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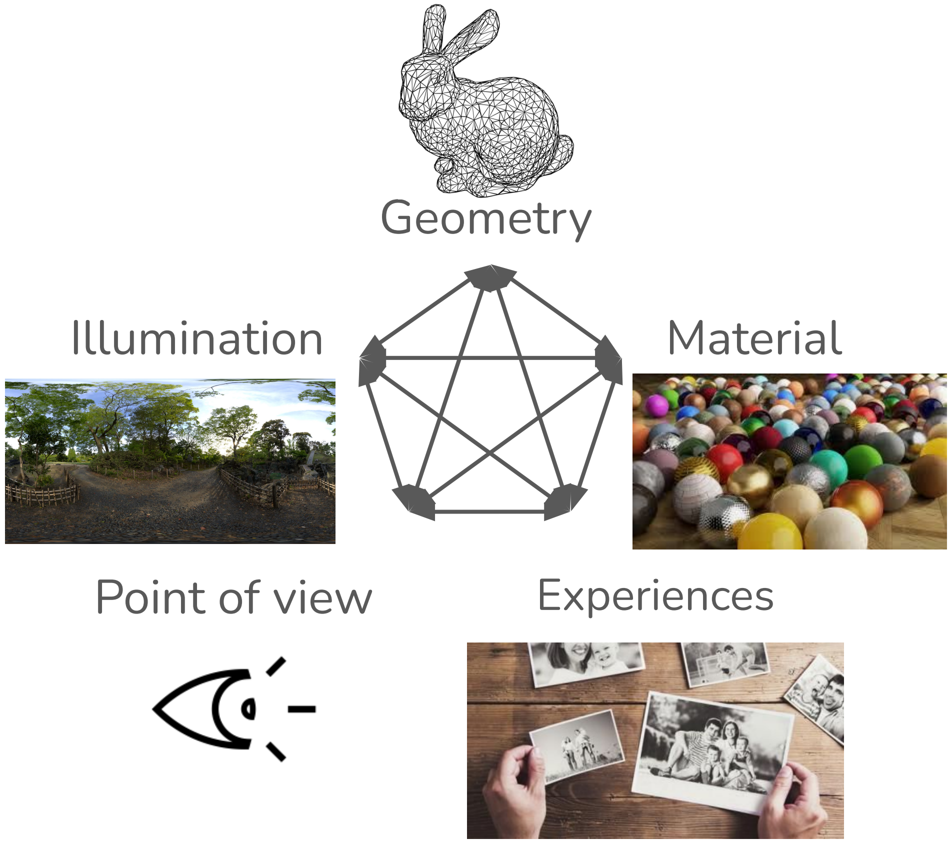
Introduction: Gloss Perception

This is because our **perception of gloss** is guided by complex interactions between:



Introduction: Gloss Perception

Same material and illumination

Different **geometry**

Introduction: Gloss Perception

Same material and illumination
Different **geometry**

[Lagunas et al. 2021]

Introduction: Gloss Perception

Same material and geometry
Different **illumination**

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Introduction: Gloss Perception

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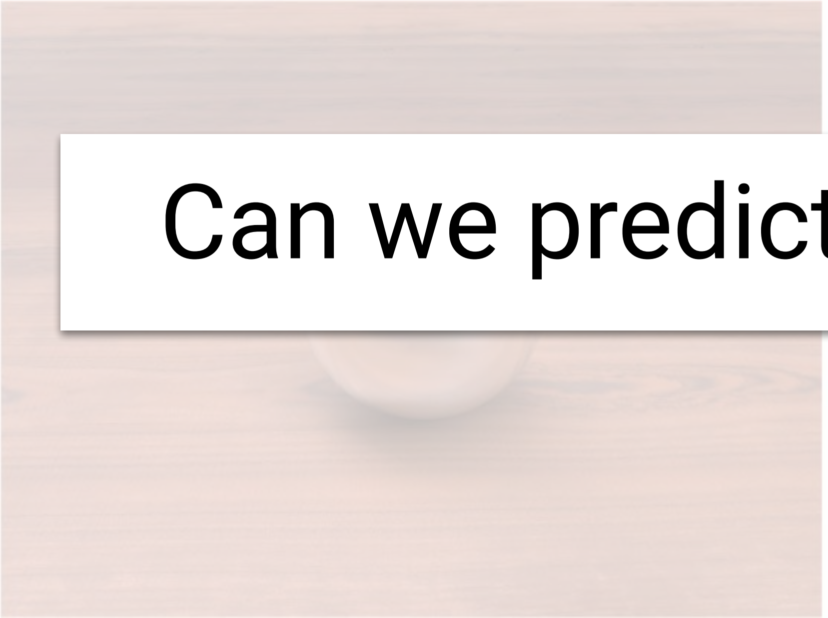

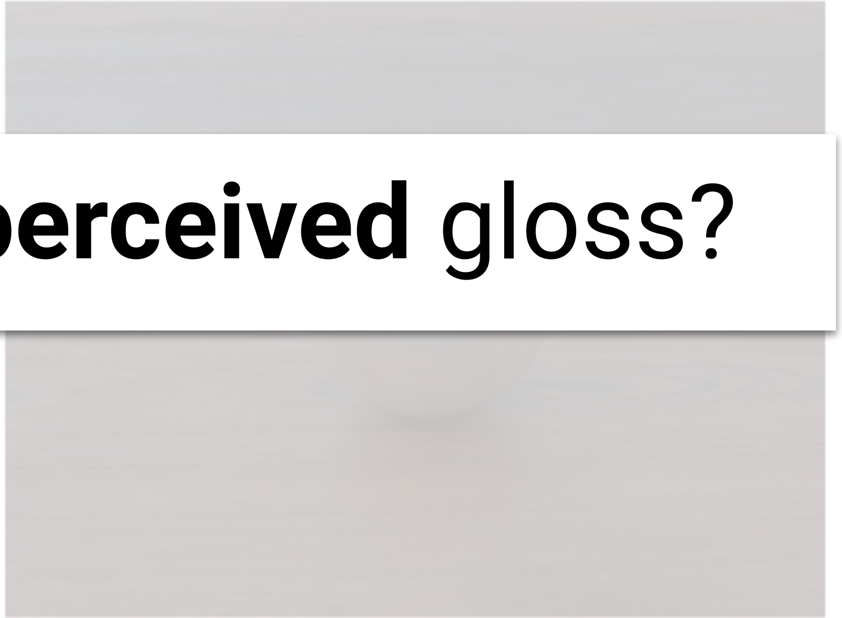

Can we predict **perceived** gloss?

[Lagunas et al. 2021]

Related Work: Gloss Perception

[Wills et al. 09] *Toward a perceptual space for gloss*

[Fleming 12] *The influence of Fresnel effects on gloss perception*

[Adams et al. 18] *Naturally glossy: Gloss perception, illumination statistics, and tone mapping*

[Faul et al. 19] *The influence of Fresnel effects on gloss perception*

Related Work: Objective Measurements

Since the publication of **Hunter et al. [1937]** it has been recognized that a single physical measurement is not sufficient to quantify perceived “gloss”

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Multiple proposals have been made:

BRDF parameters (e.g., [Pellacini et al. 00])

Image statistics (e.g., [Motoyoshi et al. 07])

Industry standards (e.g., [Westlund and Meyer 01])

Related Work: Learning-based Methods

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Learning-based methods require **data**

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Datasets:

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[Shi et al. 21] **30 100** human annotations
[Lavoué et al. 21] **84 138** human annotations
[Delanoy et al. 22] **39 000** human annotations

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Datasets:

We seek a **reduction** of the human annotation **costs**

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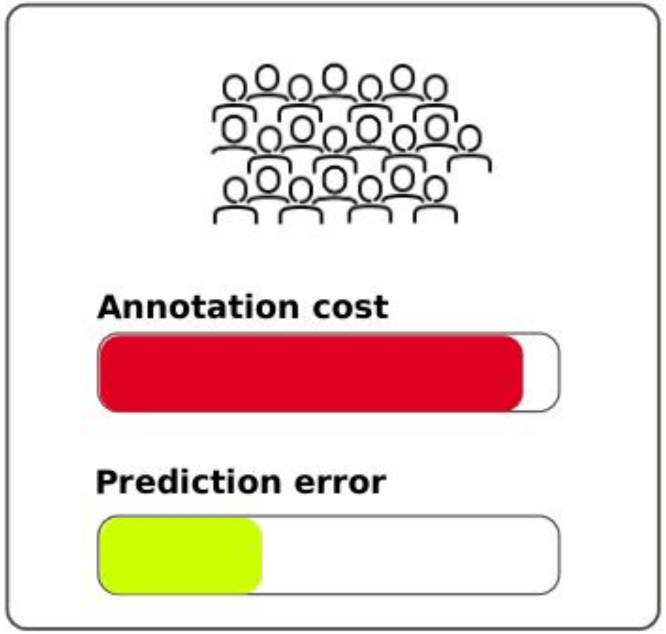
Goal

Traditional Approaches



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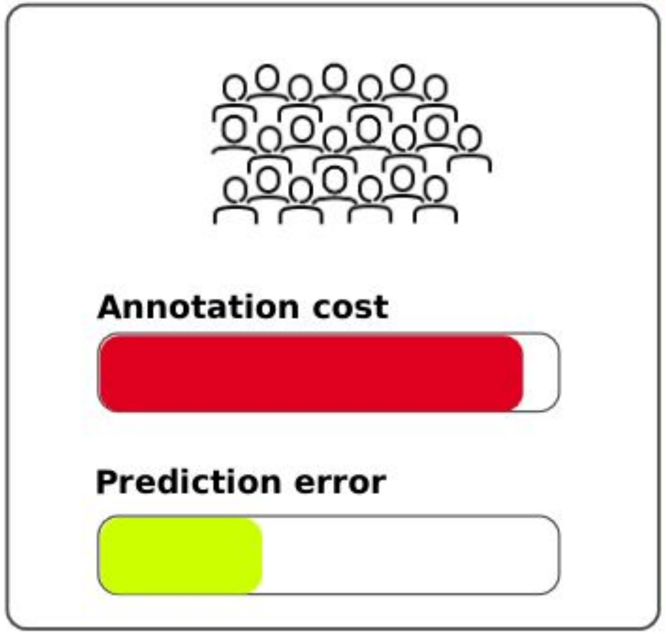
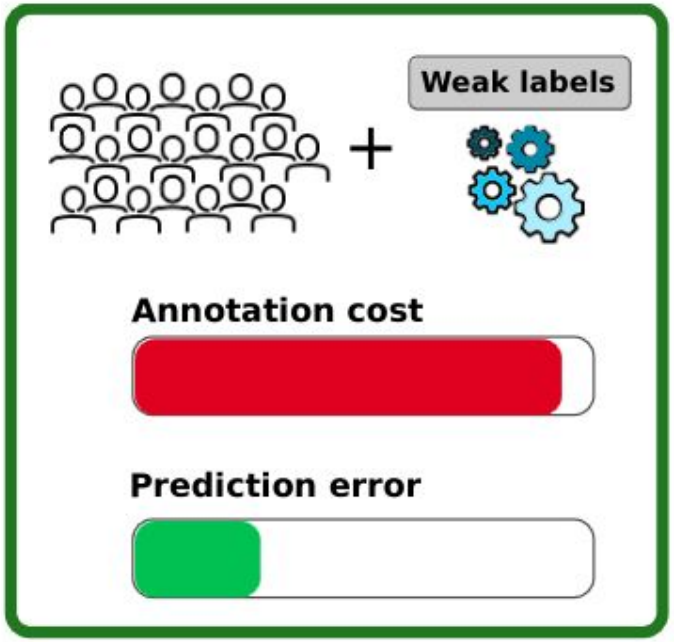


Our Work



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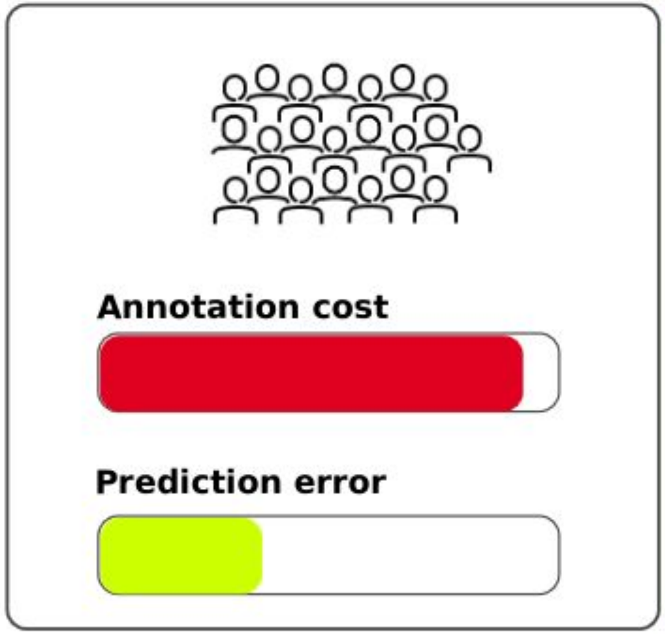

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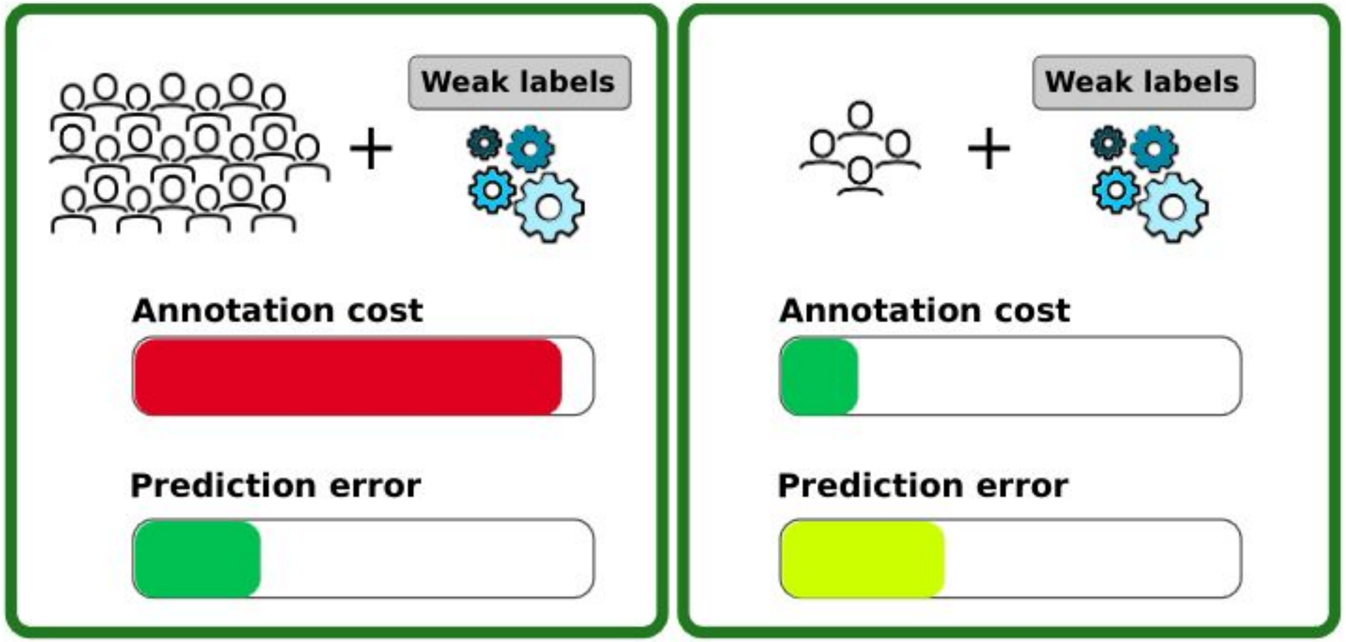

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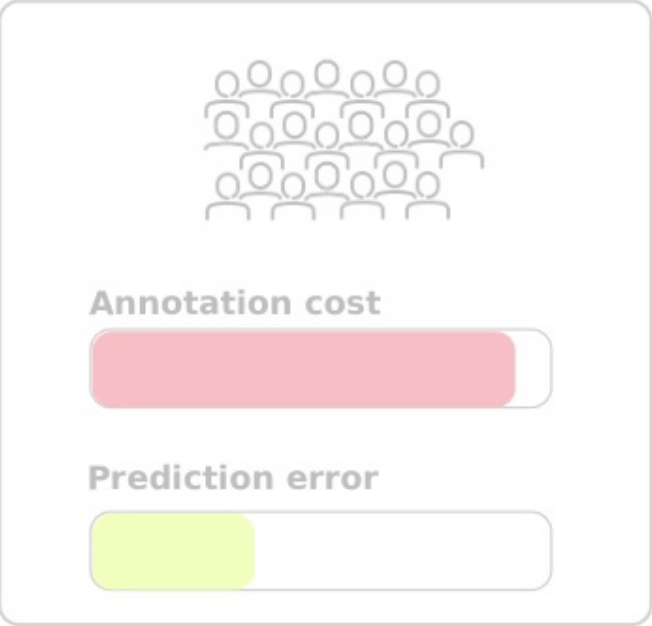

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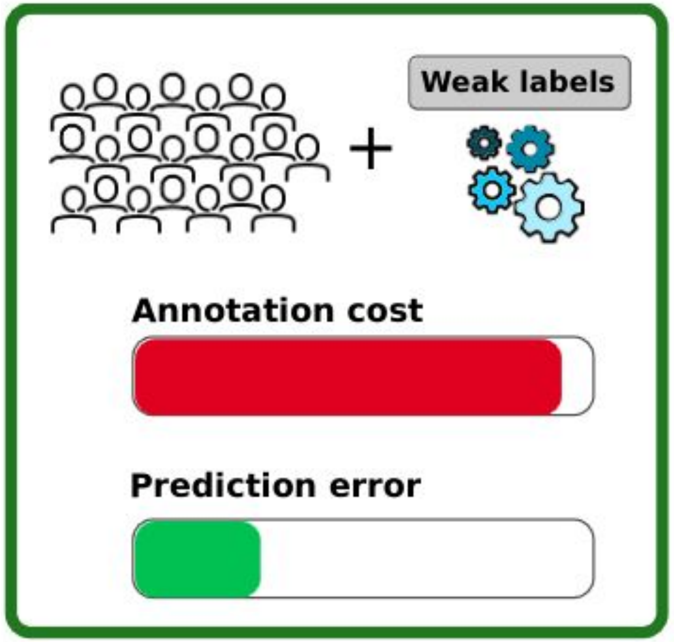
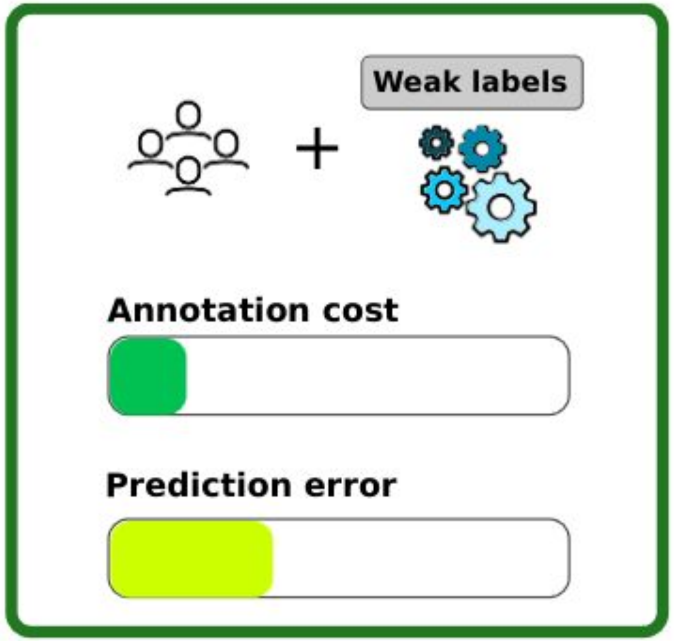
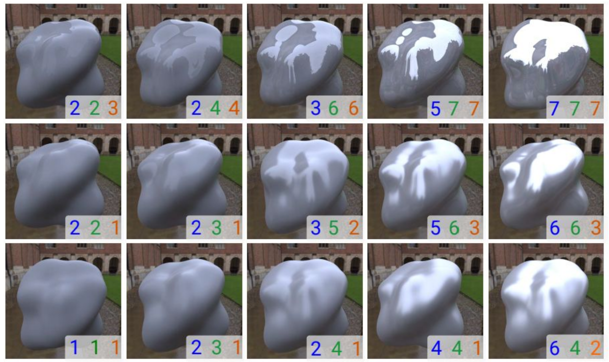


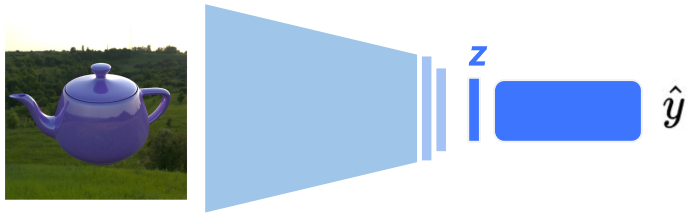


Overview

Dataset and Weak Labels



Gloss Predictor



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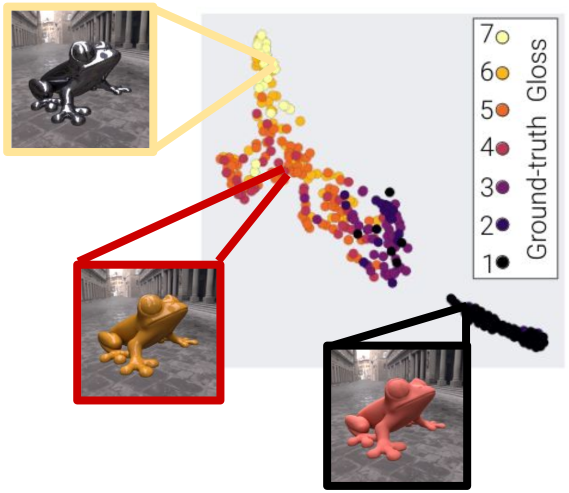
Results



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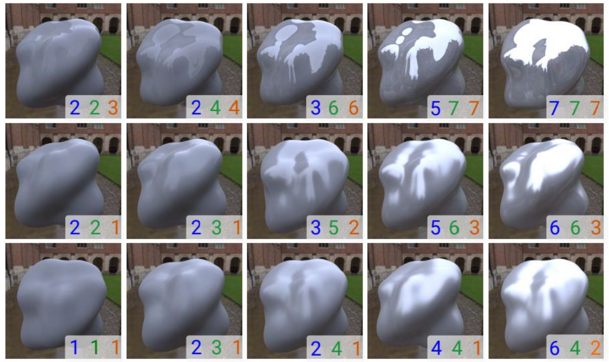

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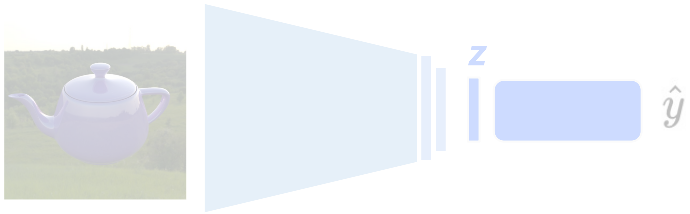

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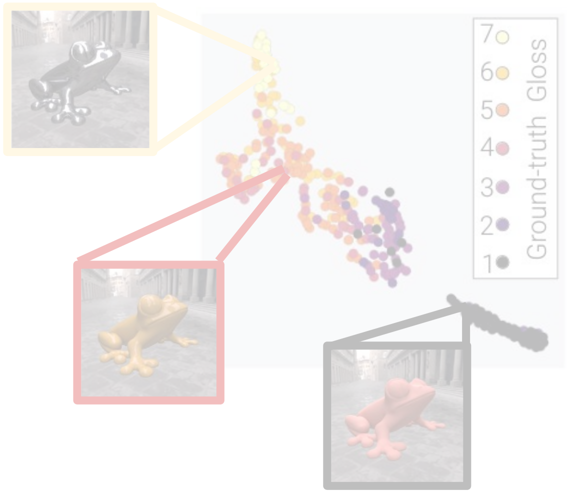

Our Dataset: Scene Parameters

15 Geometries

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17 Illuminations

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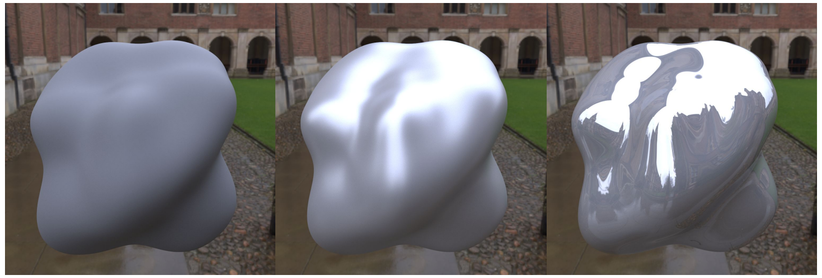
50 BSDF variations



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38 250 Total Images

3 Random colors and rotations

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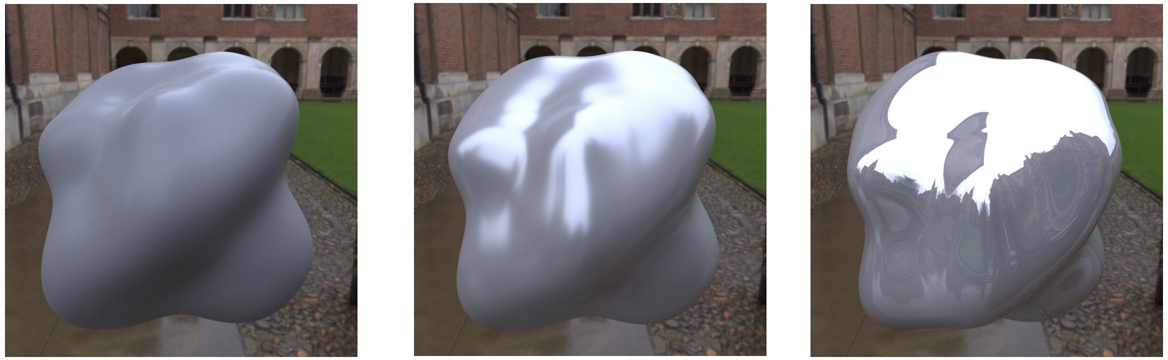
- **Disney BSDF**
- **Image Statistics**
- **Industry Standards**

Our Dataset: Weak Labels

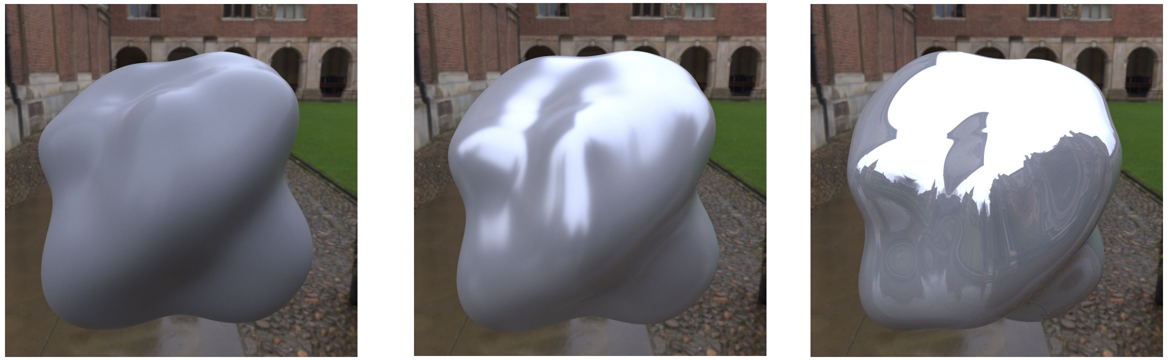
- Disney BSDF



- Image Statistics
- Industry Standards

Our Dataset: Weak Labels

- **Disney BSDF**
  - Weighted combination f of roughness (r) and specular (s) parameters [Adams et al. 18]



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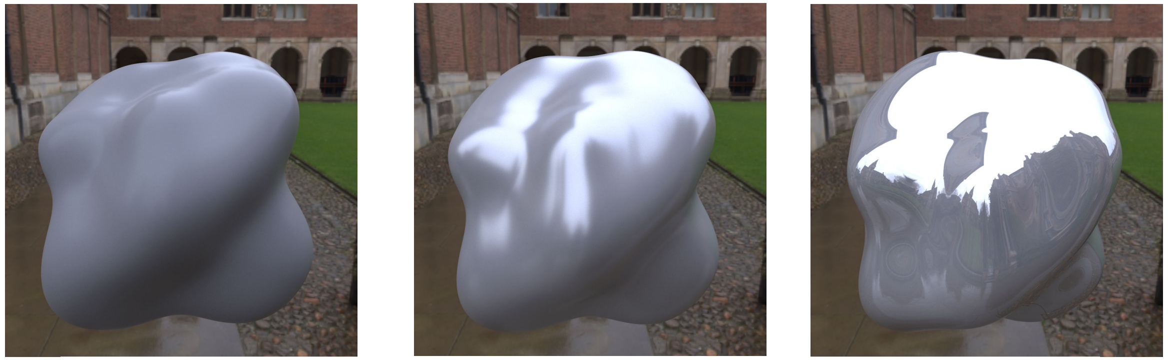

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- **Image Statistics**
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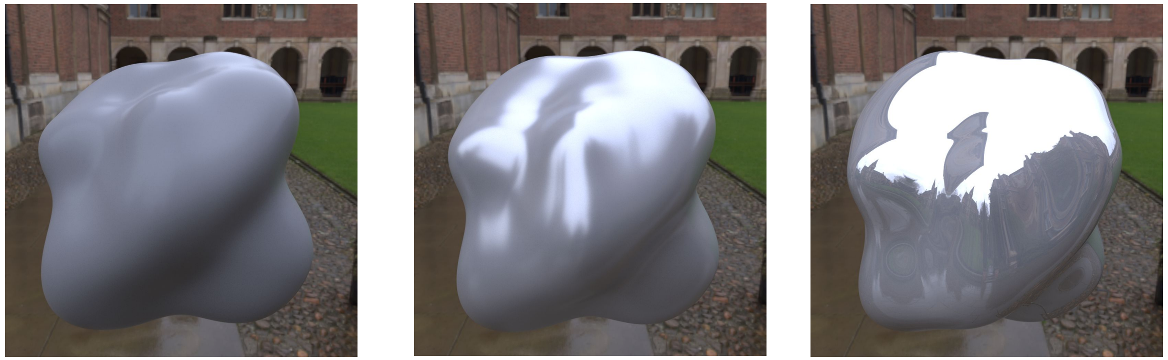
- **Industry Standards**
  - Log ratio at 20º between the reflectances of black glass (r_g) and Disney BSDF (r_d) [Westlund and Meyer 01]



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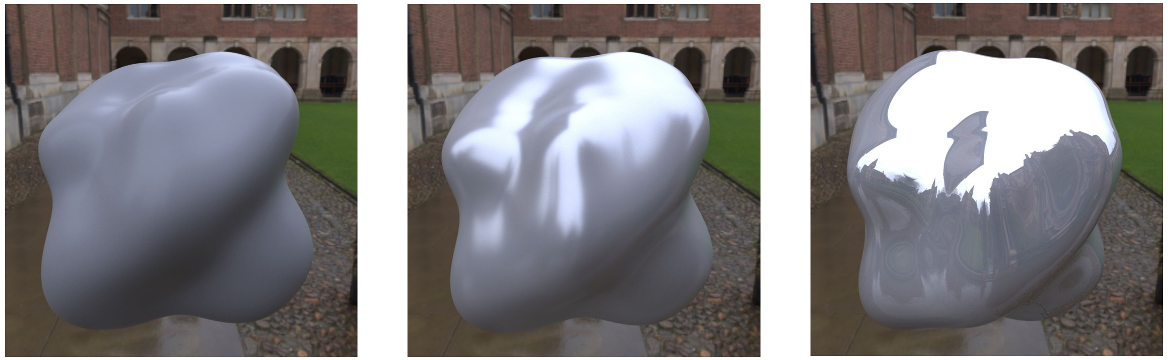

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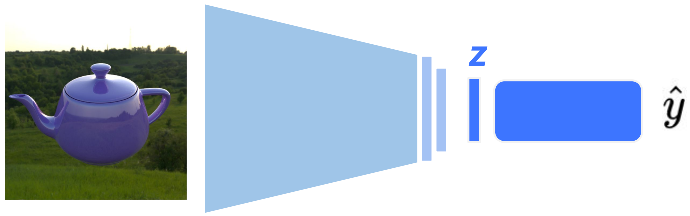

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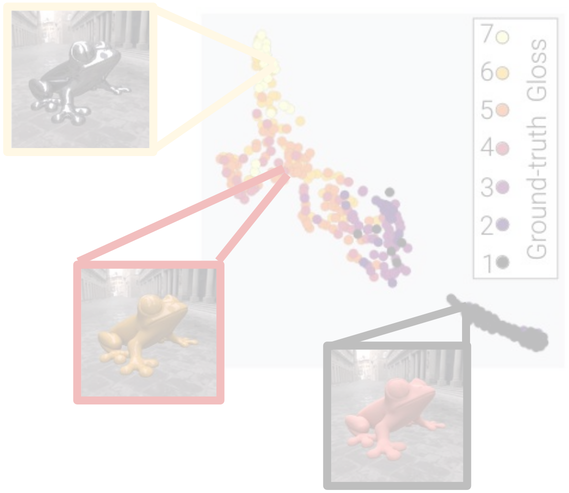
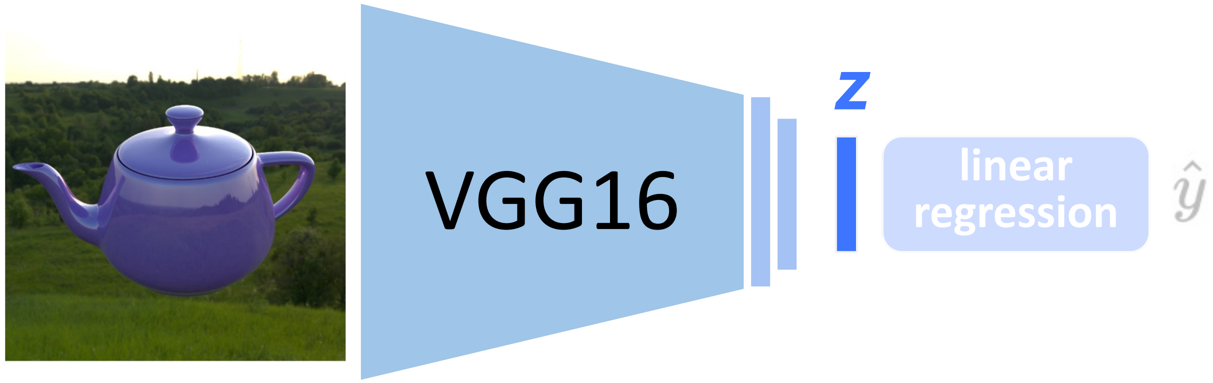


Gloss Predictor

Adapted **VGG16** architecture to a 20D **latent space** ***z***

Linear regression



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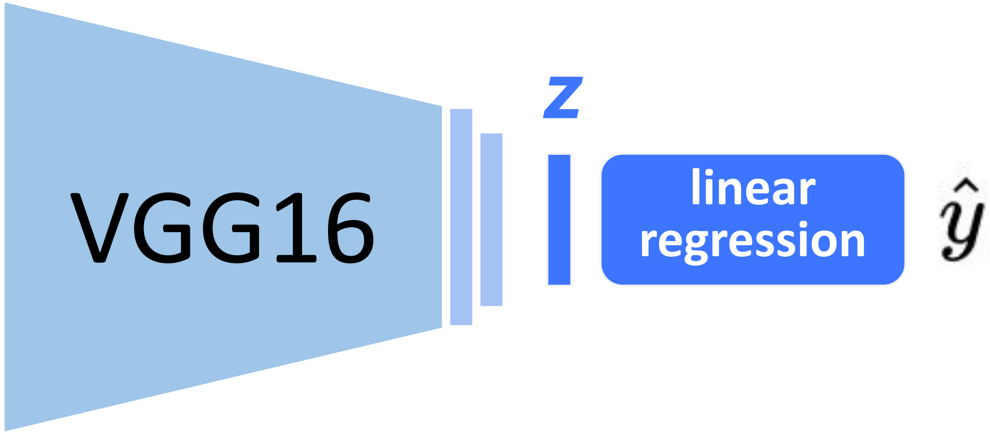
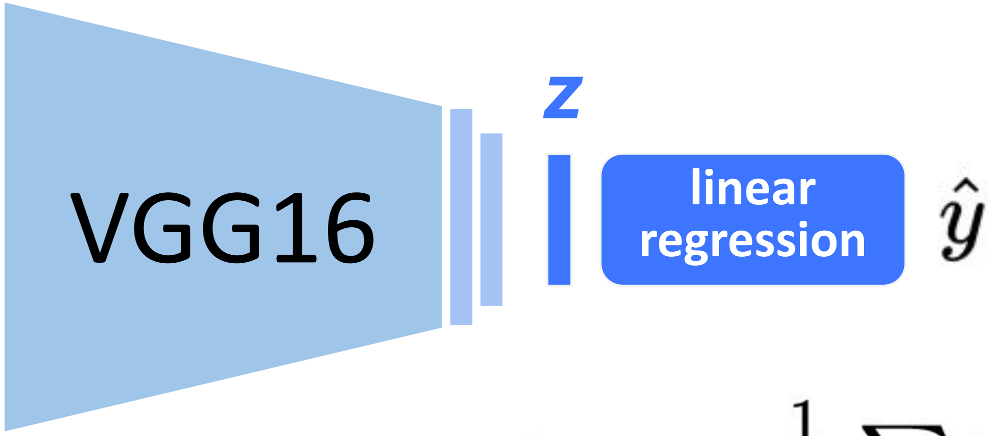
Gloss Predictor: Training



Gloss Predictor: Training

Minimize **Mean Absolute Error** (MAE)



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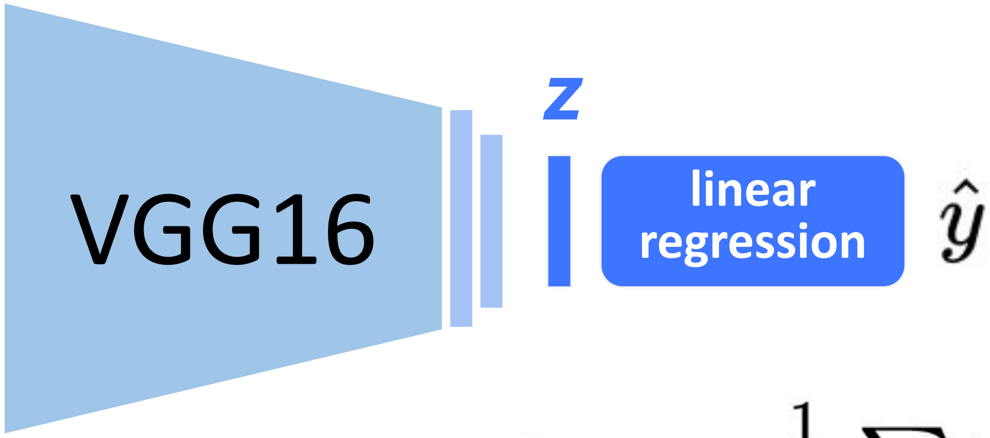

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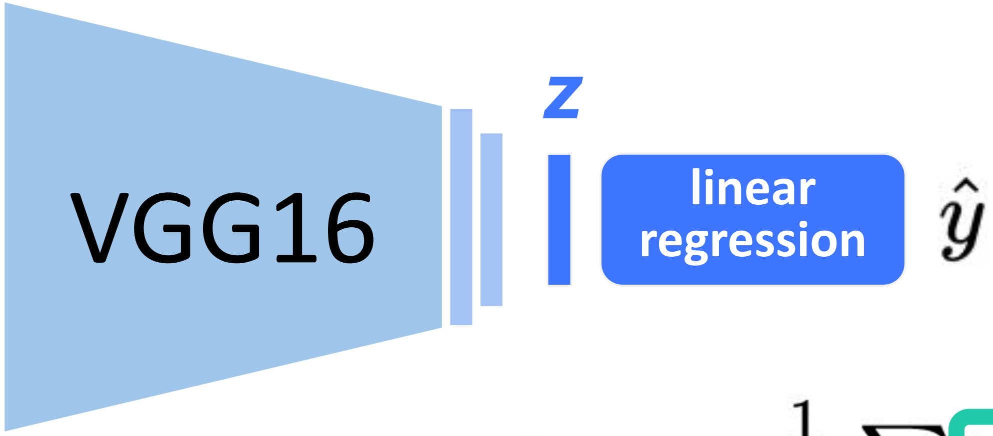

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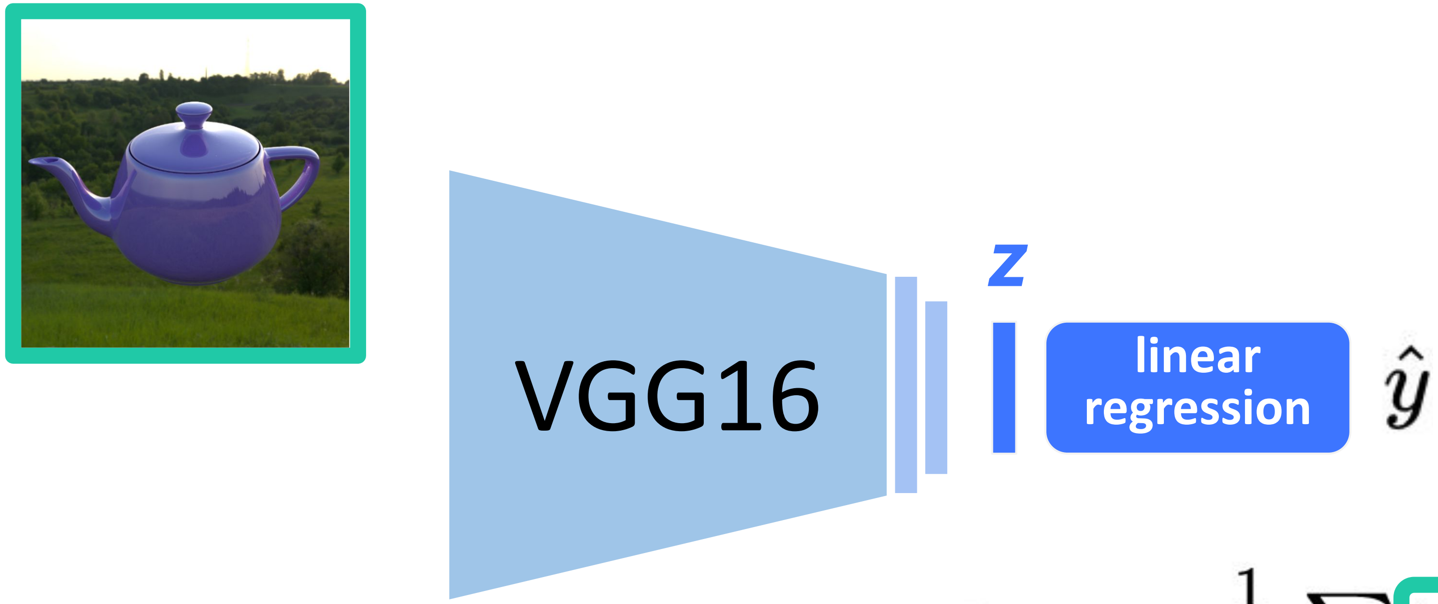

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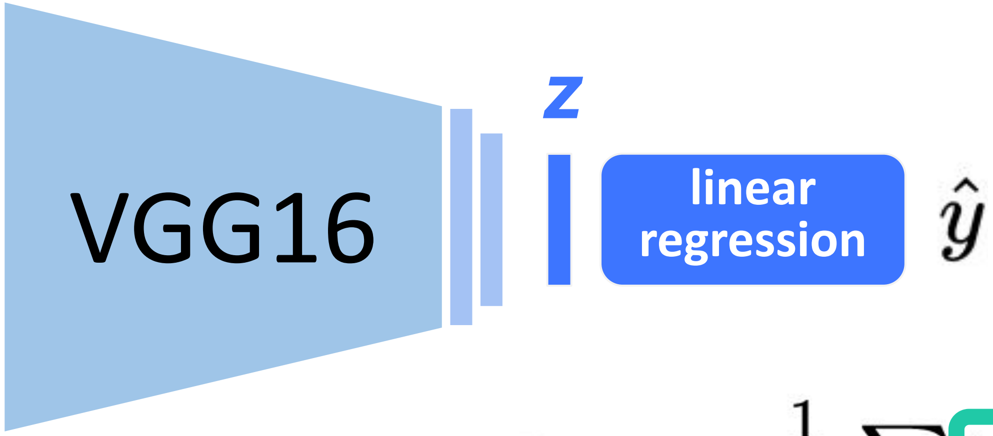
Manual annotation from humans [Serrano et al. 2021]



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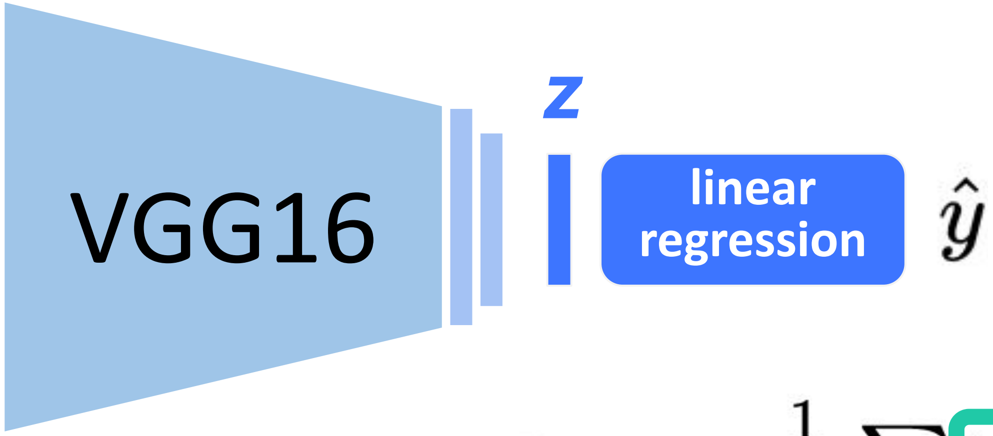
Objective metric of gloss (Ours)



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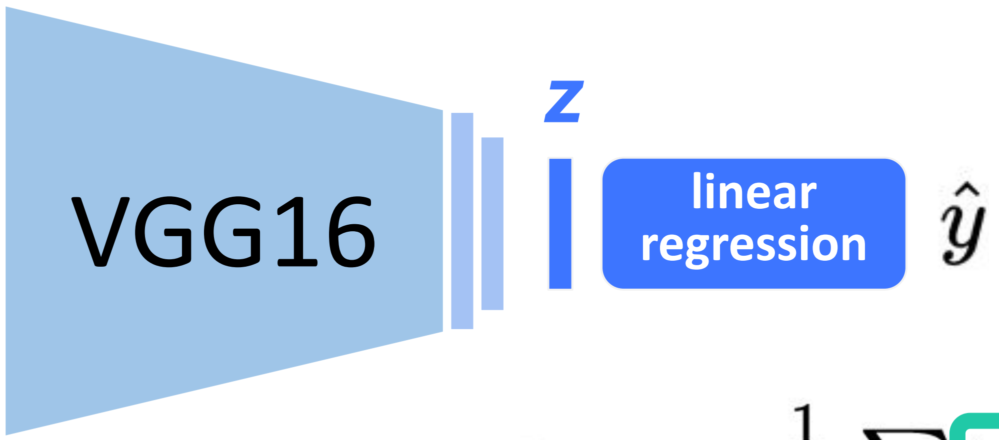

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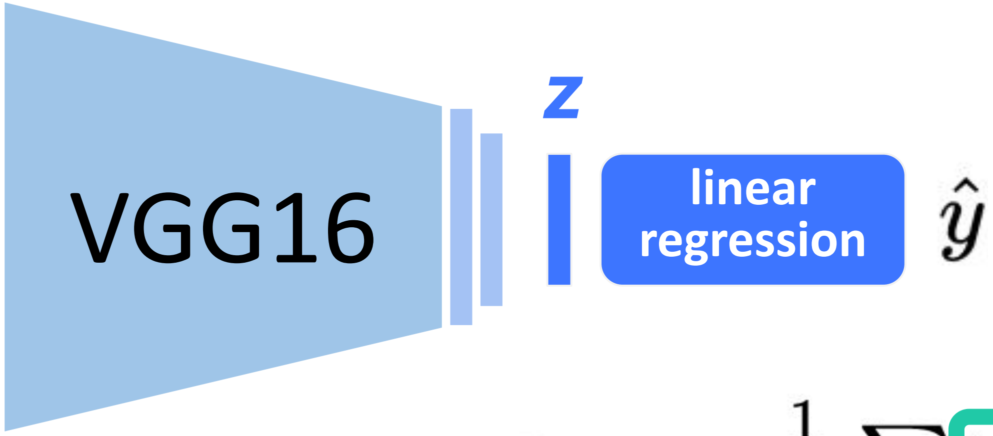

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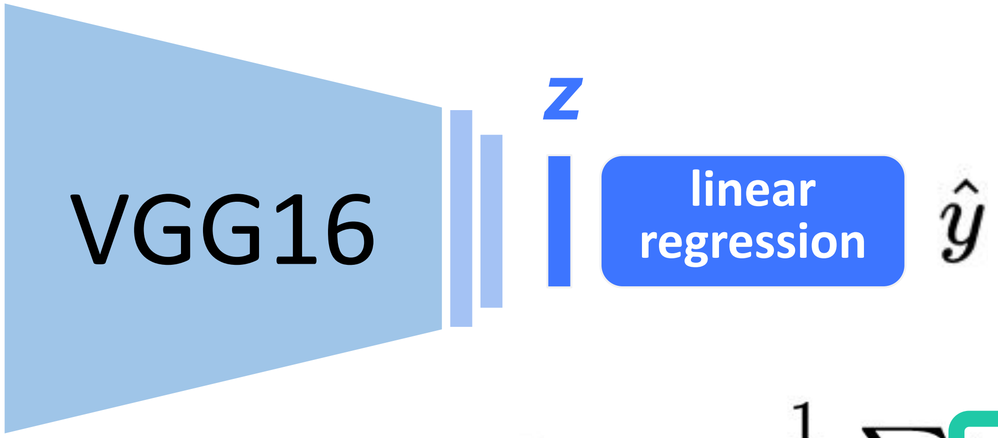

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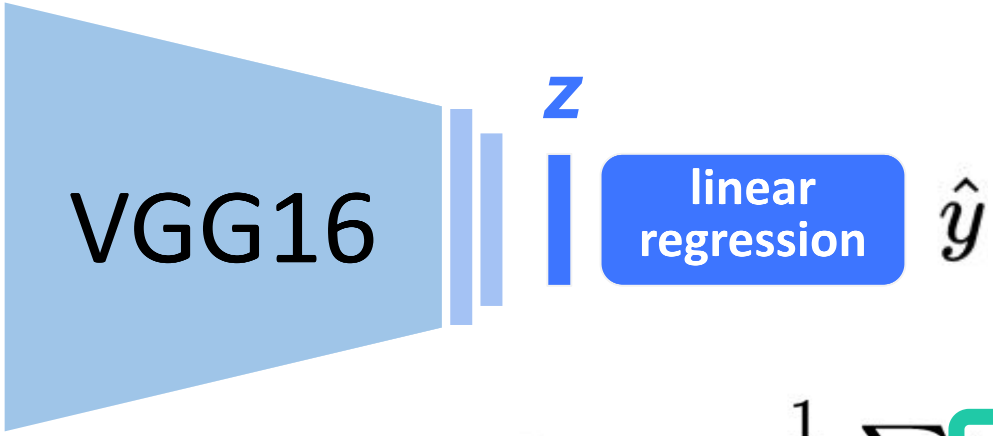

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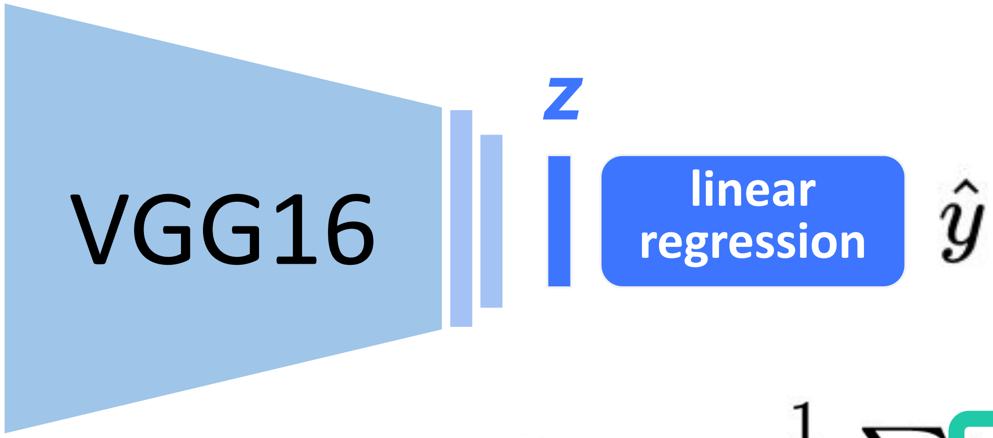

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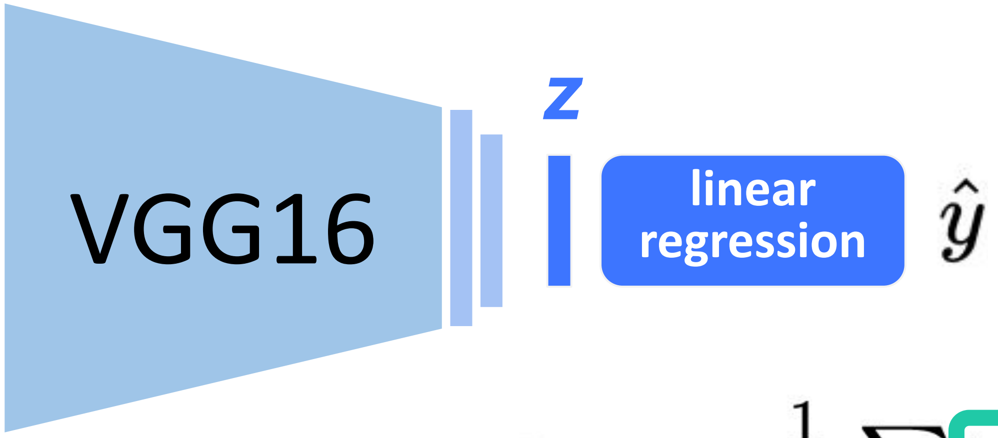

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Gloss Predictor: Evaluation

Test Dataset

- 310 images: Different geometries and five measured materials
- **Controlled** variations:
  A) Rotations
  B) Geometry complexity
  C) Illumination frequency
  D) Specularity
- **Reliable** annotations

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- 310 images: Different geometries and five measured materials

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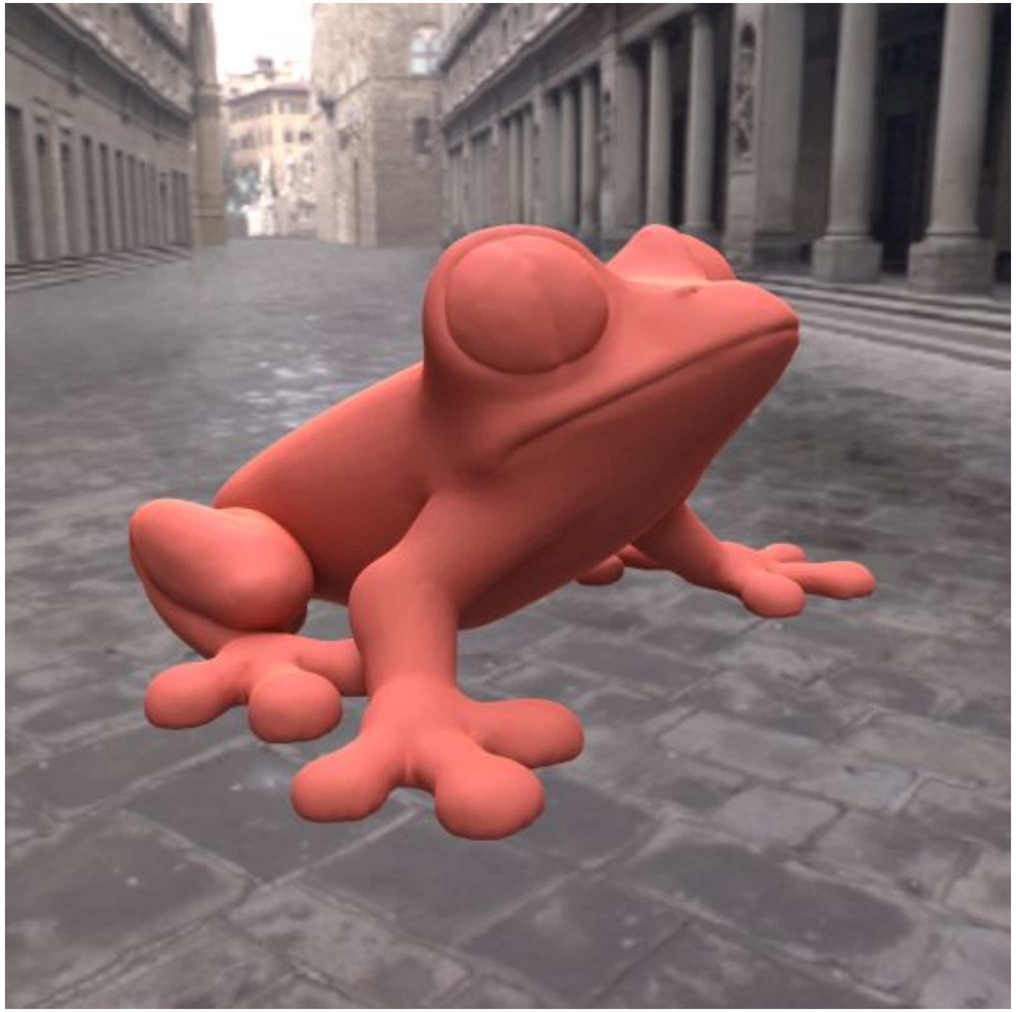

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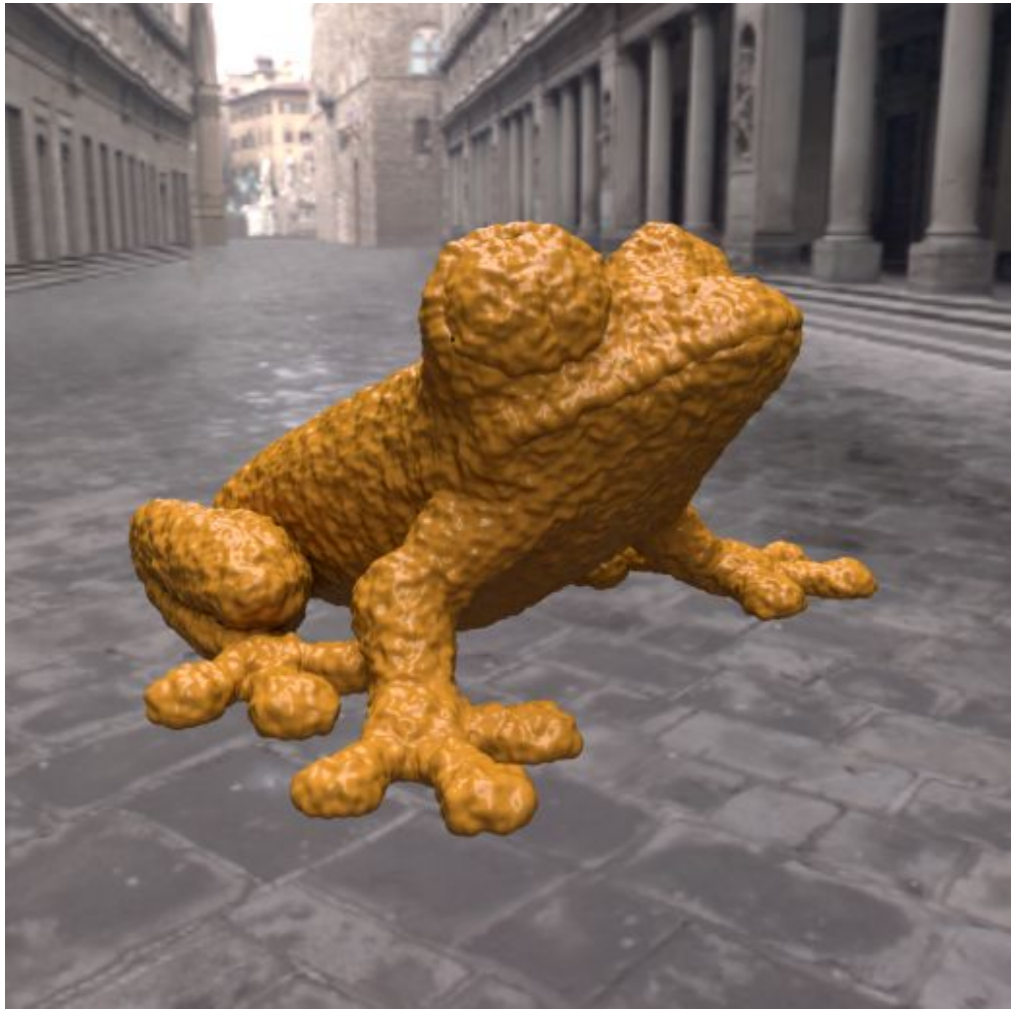

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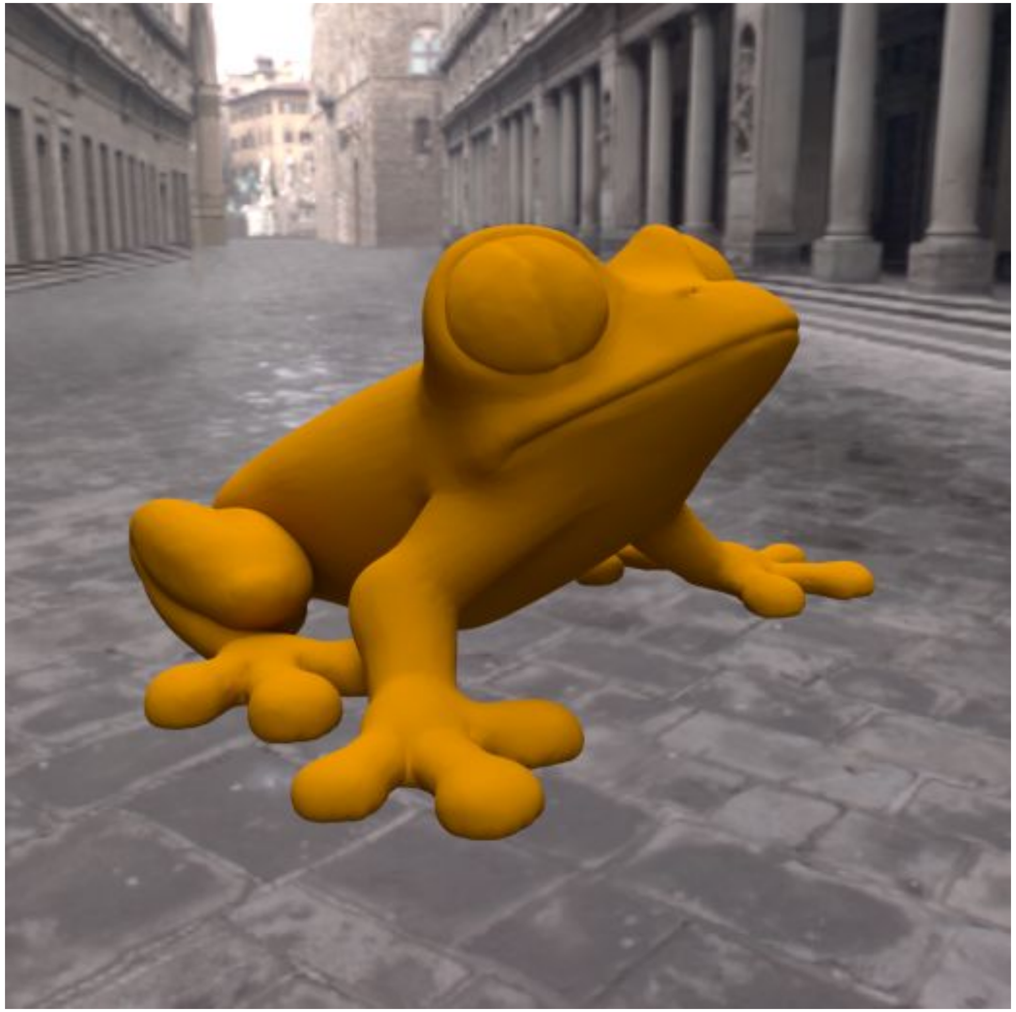

Gloss Predictor: Evaluation

Test Dataset

- 310 images: Different geometries and five measured materials

- **Controlled** variations:

  A) Rotations
  B) Geometry complexity
  C) Illumination frequency
  D) Specularity

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  D) Specularity

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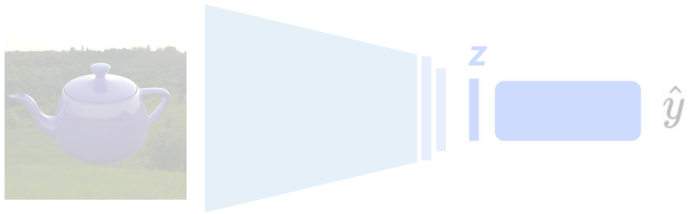
Overview

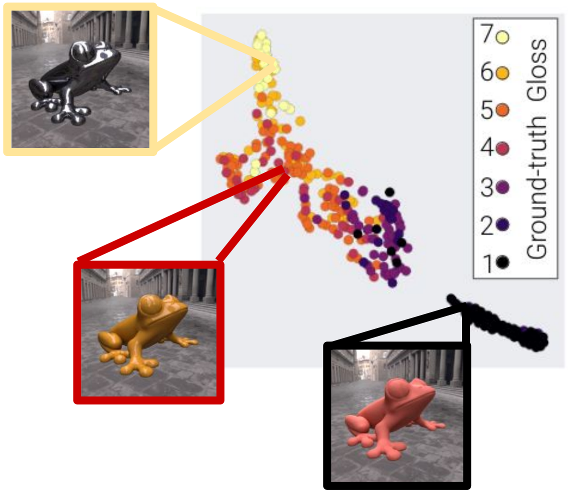
Dataset and
Weak Labels

Gloss
Predictor



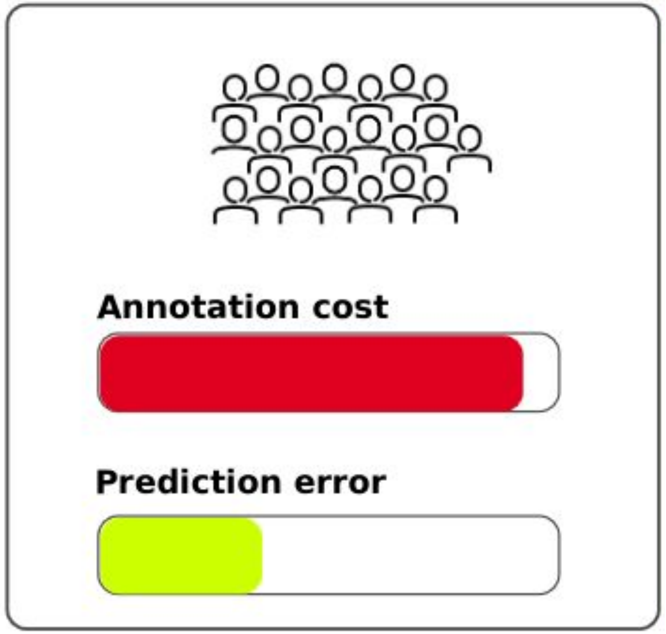
$$L_{MAE} = \frac{1}{N}\sum |y - \hat{y}|$$

Results

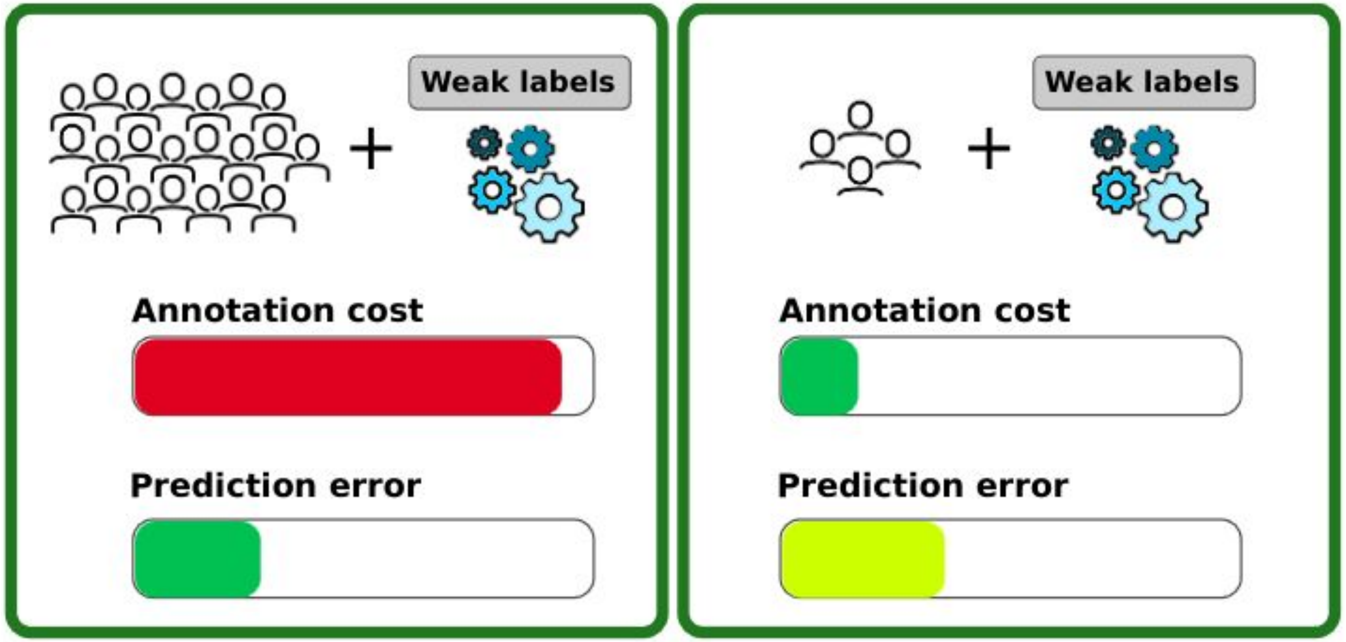


Results

Traditional Approaches



Our Work



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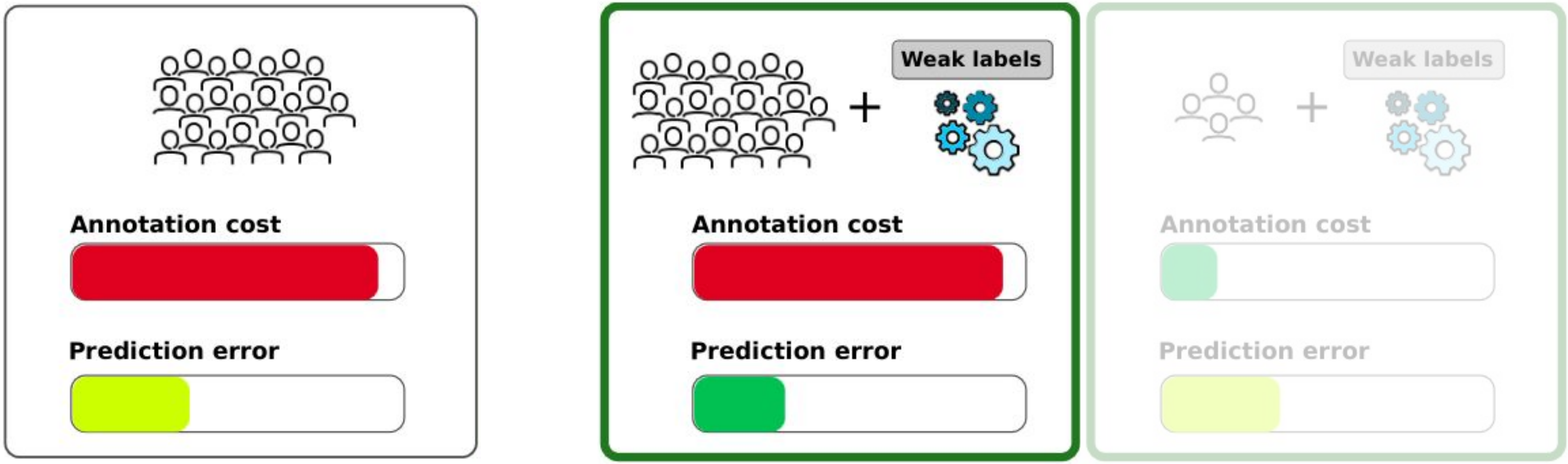

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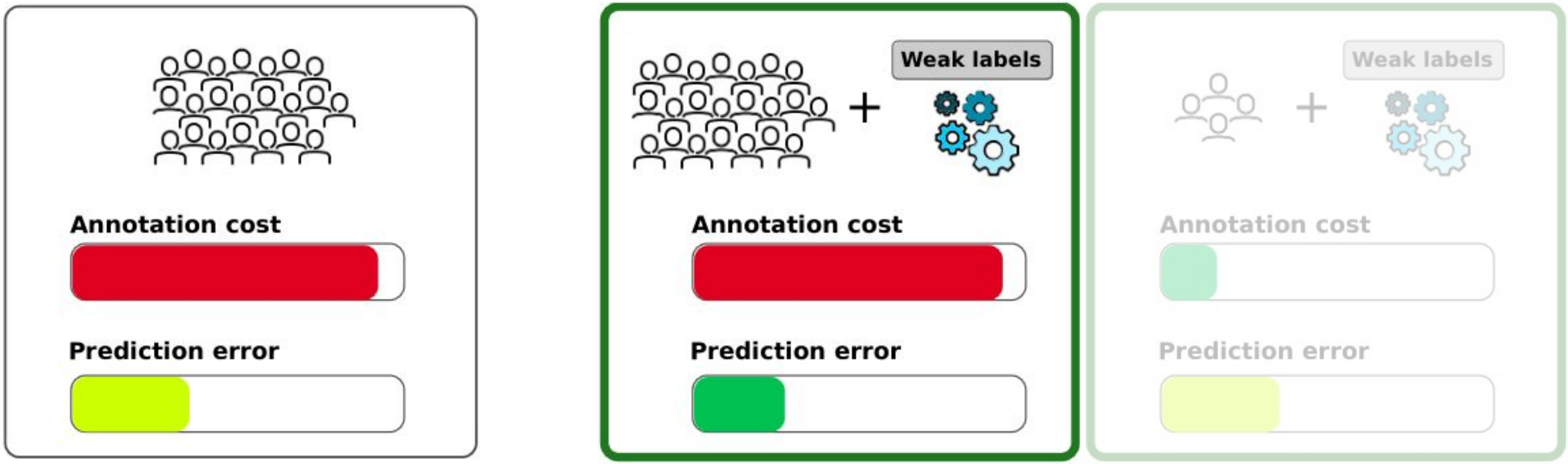
Our Work



Same annotation cost, better performance

Results: Quantitative

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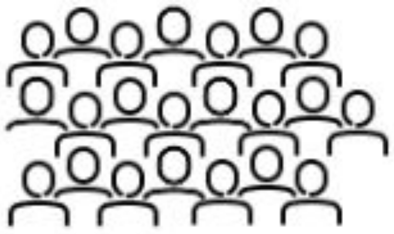
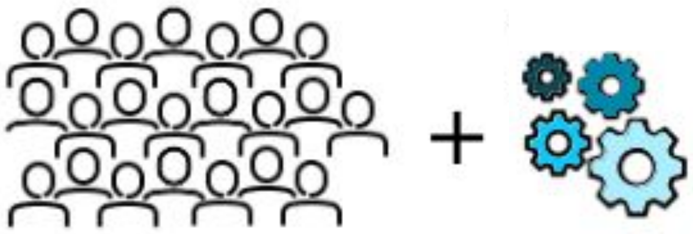
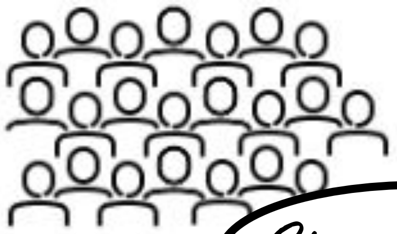


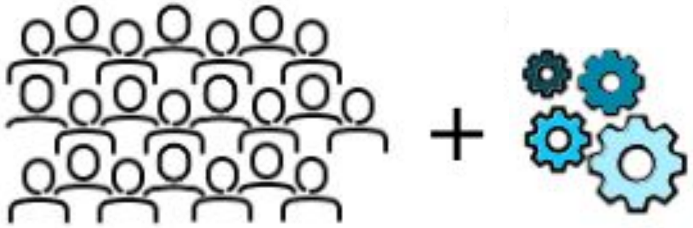


	S.100%	S.100%+BSDF	S.100%+Img.Stats.	S.100%+Industry
MAE↓				

Results: Quantitative

Same annotation cost, better performance





Strong labels

	S.100%	S.100%+BSDF	S.100%+Img.Stats.	S.100%+Industry
MAE ↓				

Results: Quantitative

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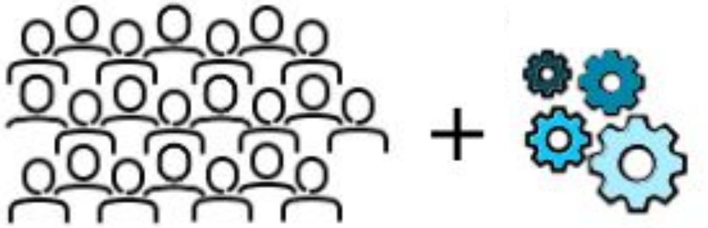
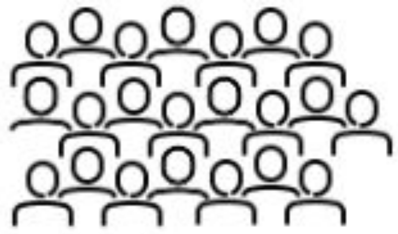
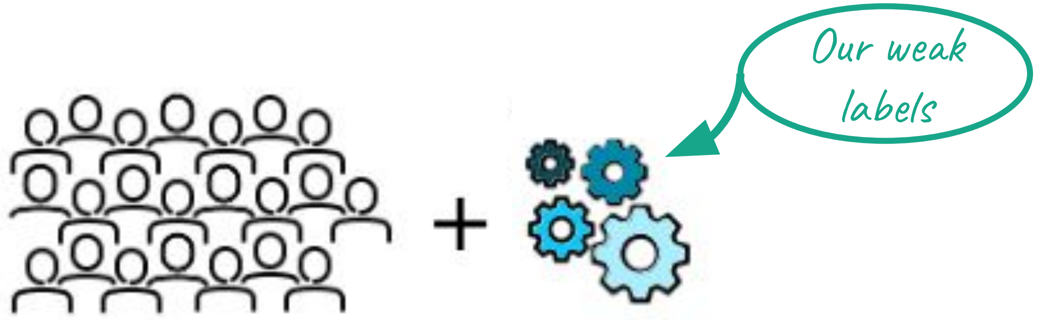


	S.100%	S.100%+BSDF	S.100%+Img.Stats.	S.100%+Industry
MAE↓	0.1510			

Results: Quantitative

Same annotation cost, better performance





	S.100%	S.100%+BSDF	S.100%+Img.Stats.	S.100%+Industry
MAE↓	0.1510			

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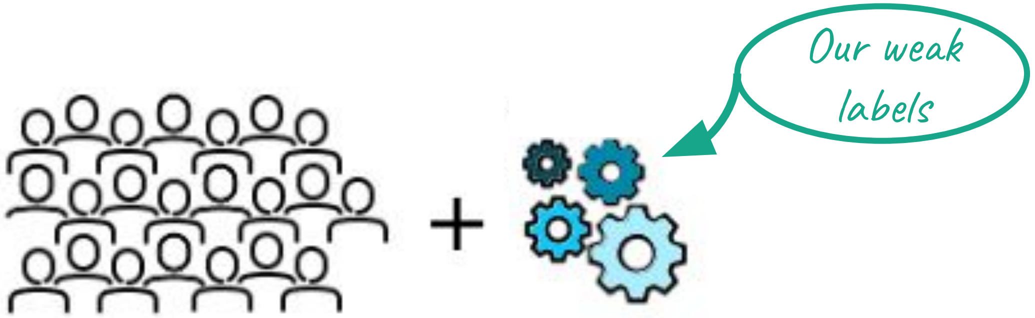
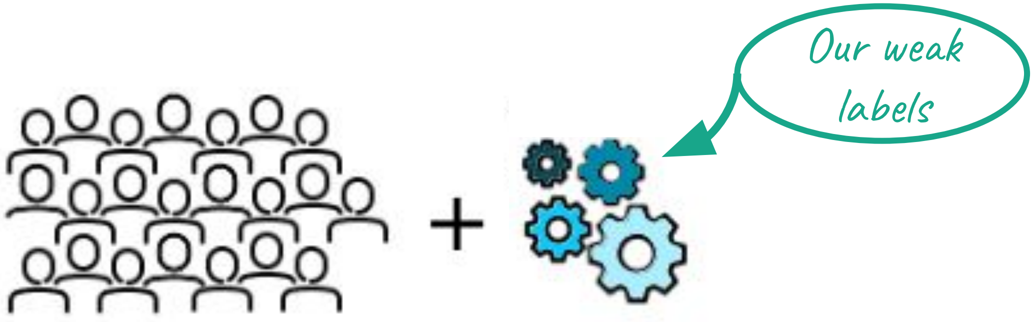


	S.100%	S.100%+BSDF	S.100%+Img.Stats.	S.100%+Industry
MAE↓	0.1510	0.1207	0.1389	0.1484

Results: Quantitative

Same annotation cost, better performance



	S.100%	S.100%+BSDF	S.100%+Img.Stats.	S.100%+Industry
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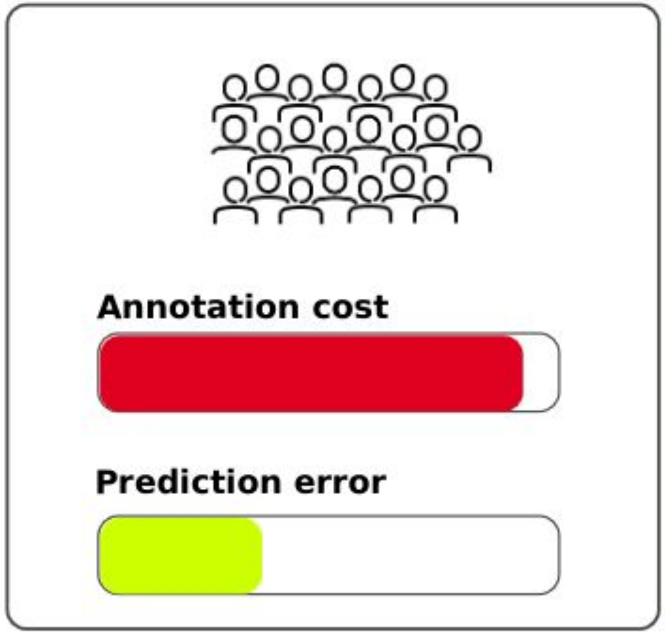
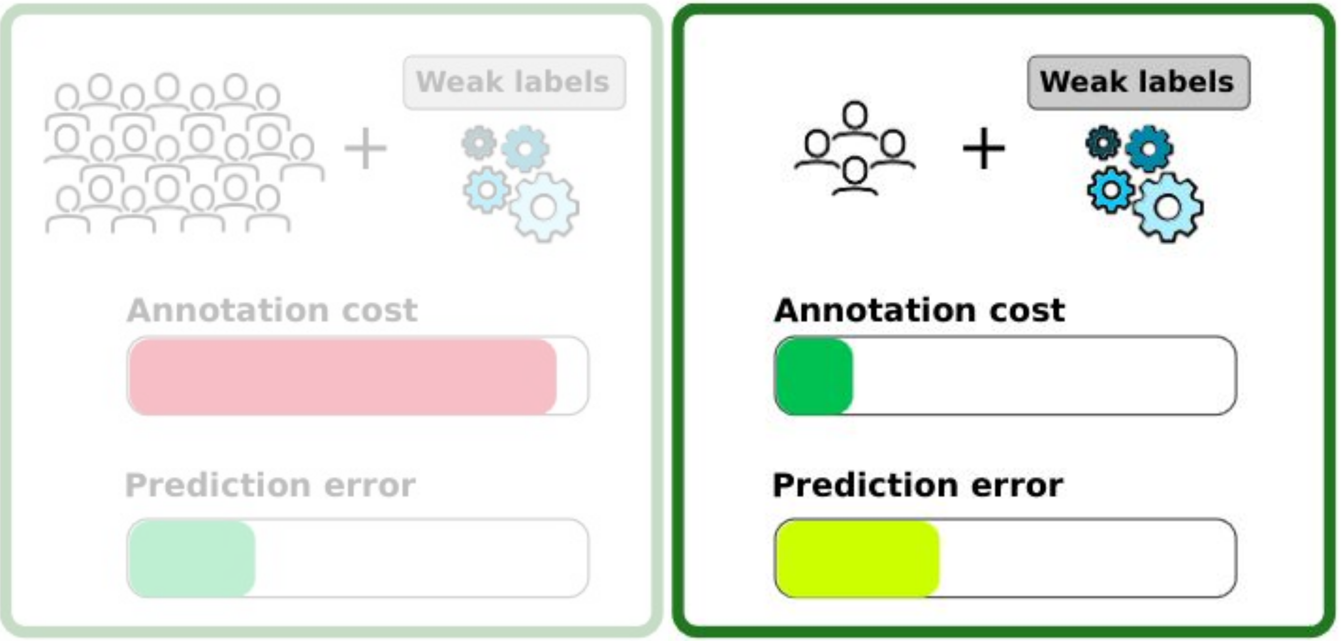


Our Work



Results: Quantitative

Traditional Approaches

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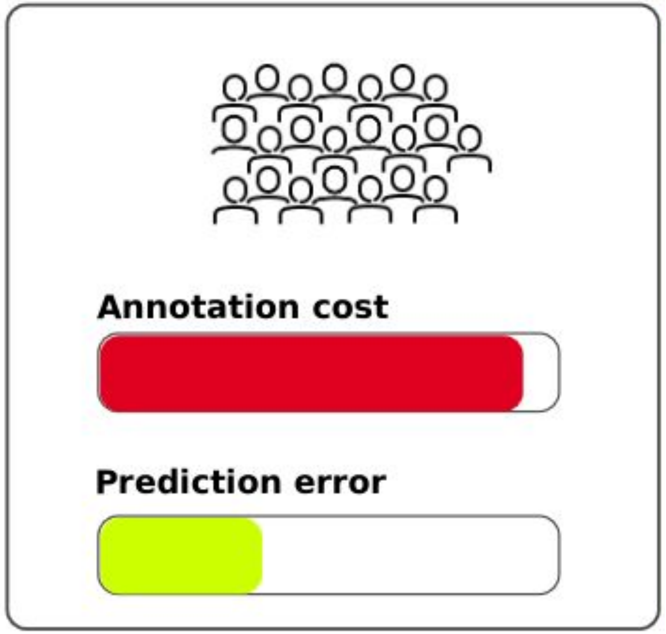

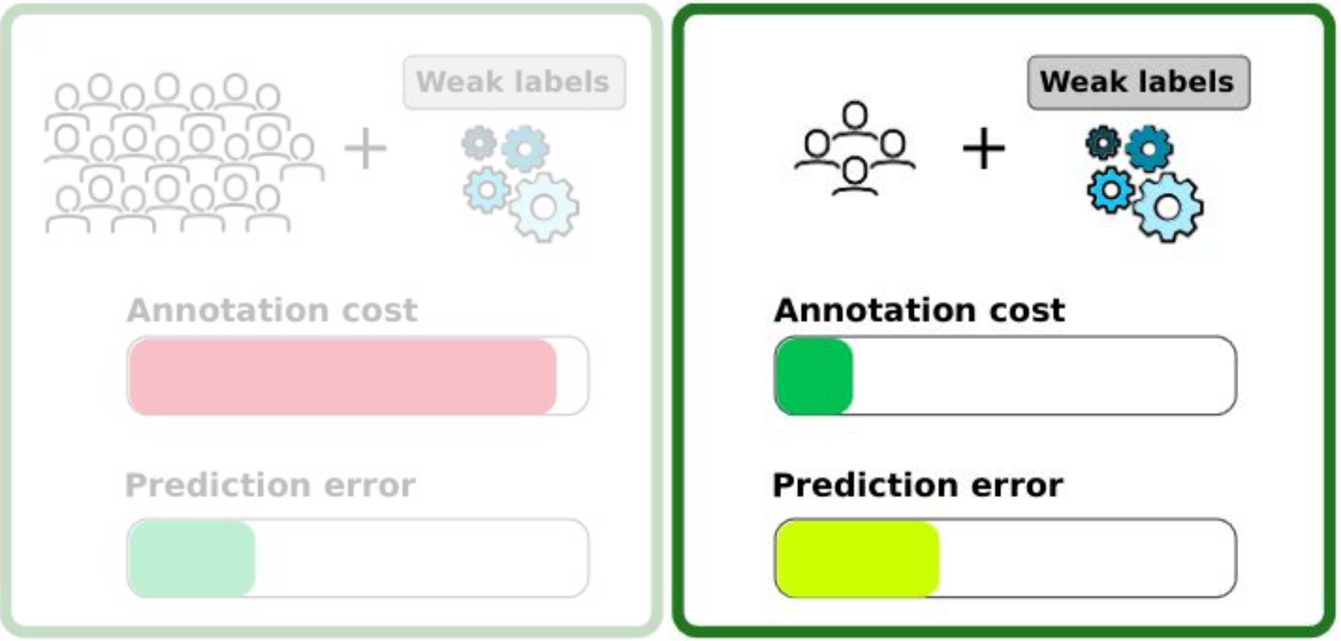

Same performance, substantially less annotation cost

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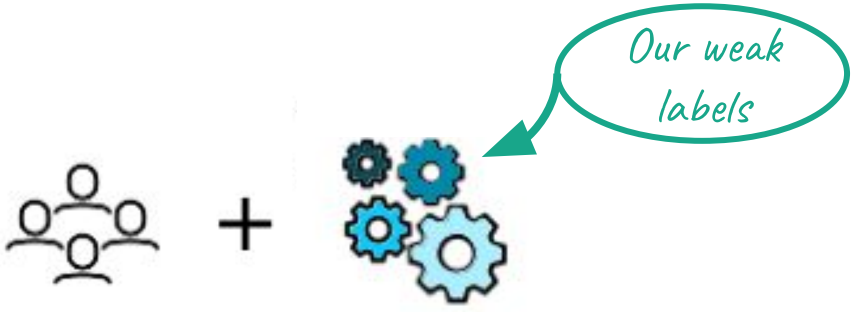

	S.100%	S.20%+BSDF	S.20%+Img.Stats.	S.20%+Industry
MAE↓				

Results: Quantitative

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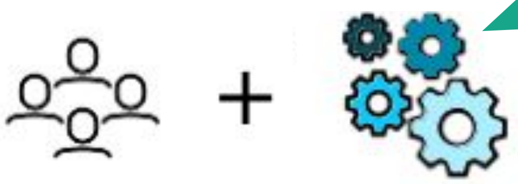
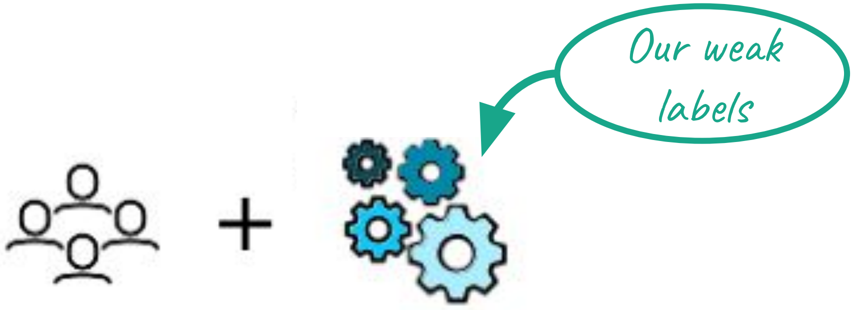


Our weak labels

	S.100%	S.20%+BSDF	S.20%+Img.Stats.	S.20%+Industry
MAE↓	0.1510			

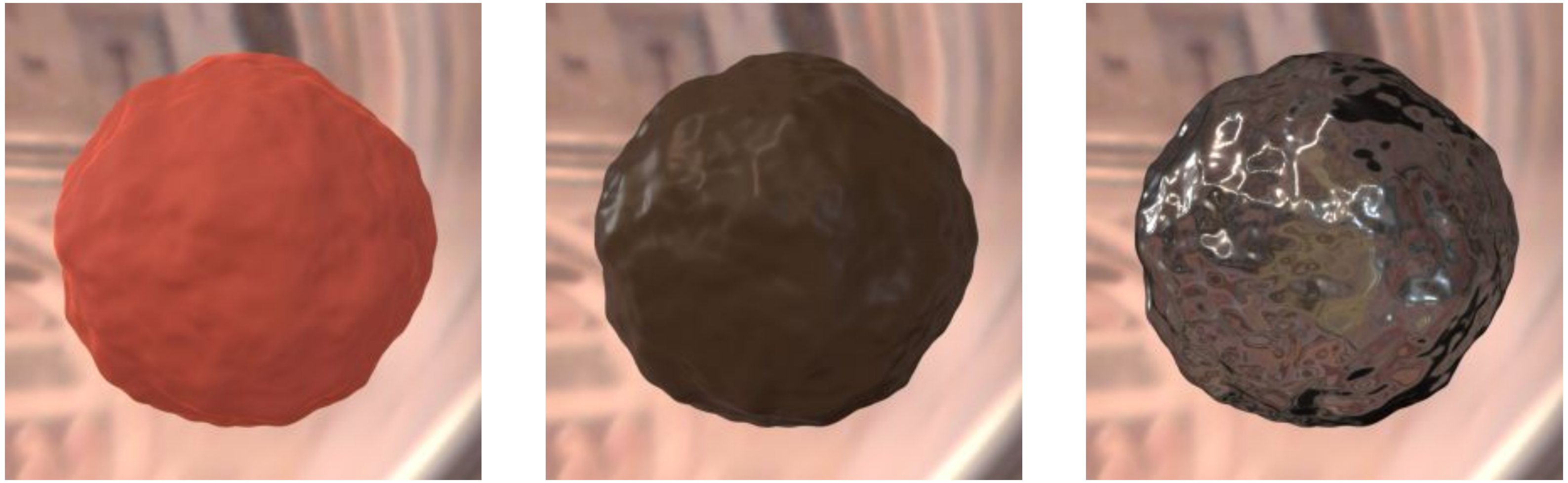
Results: Quantitative

Same performance, substantially less annotation cost



	S.100%	S.20%+BSDF	S.20%+Img.Stats.	S.20%+Industry
MAE↓	0.1510	**0.1538**	**0.1550**	0.1797

Results: Qualitative



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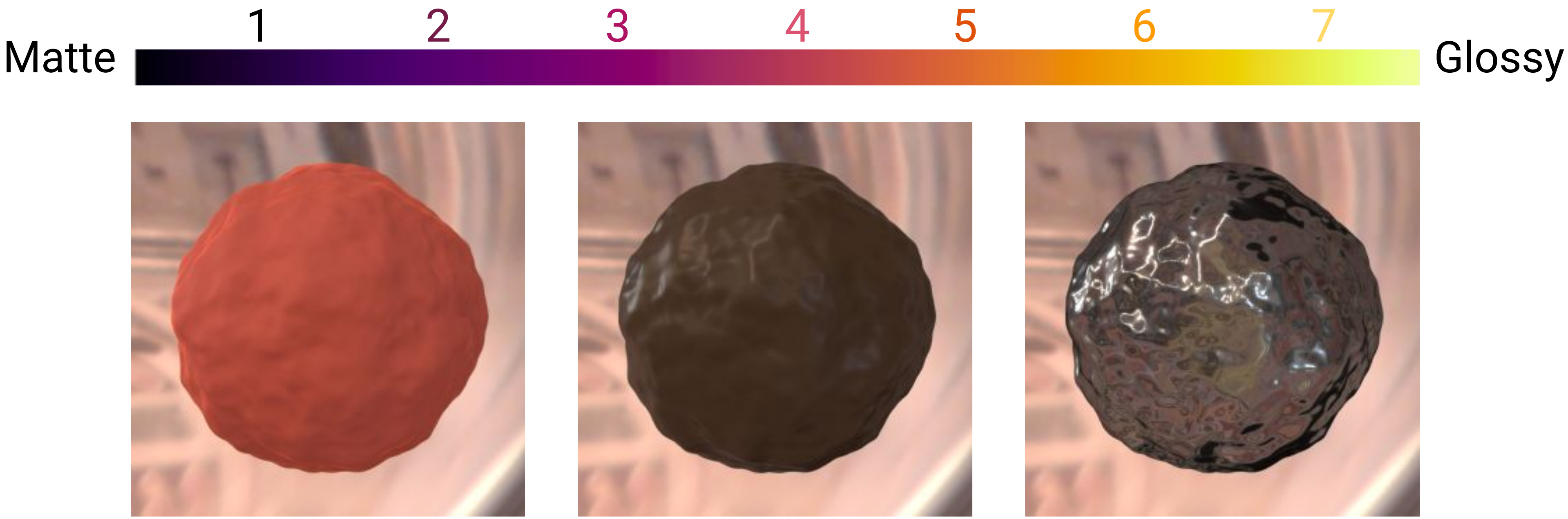
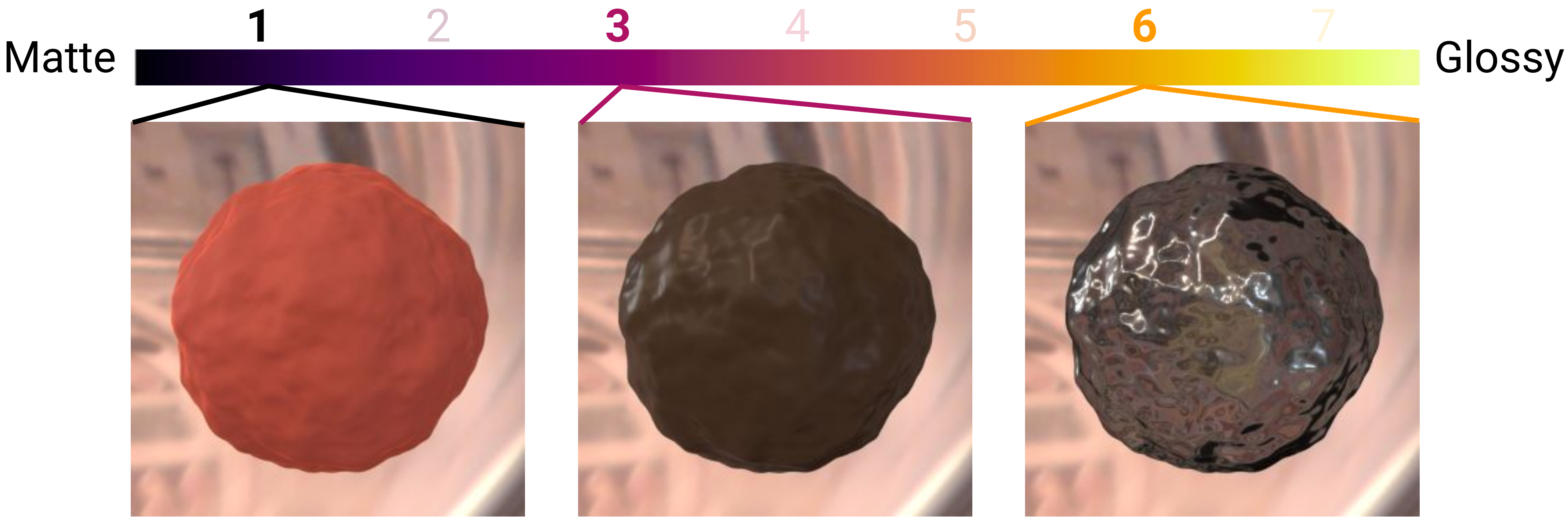


Results: Qualitative

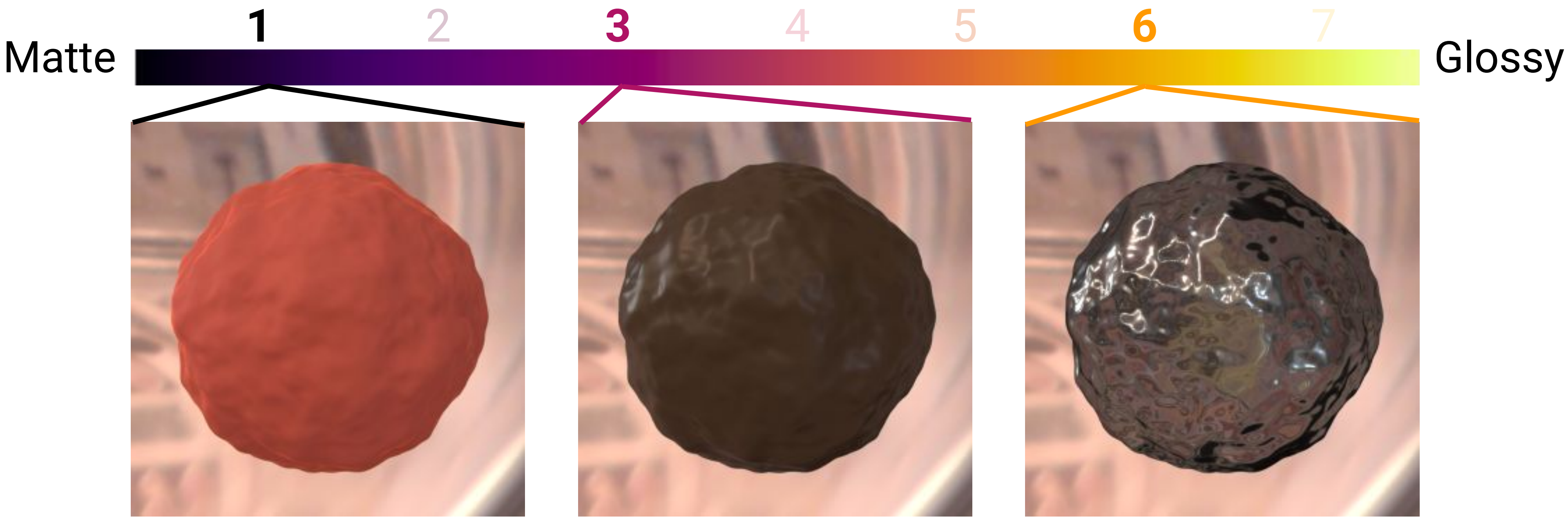


GT	1.00	3.00	6.00

Results: Qualitative

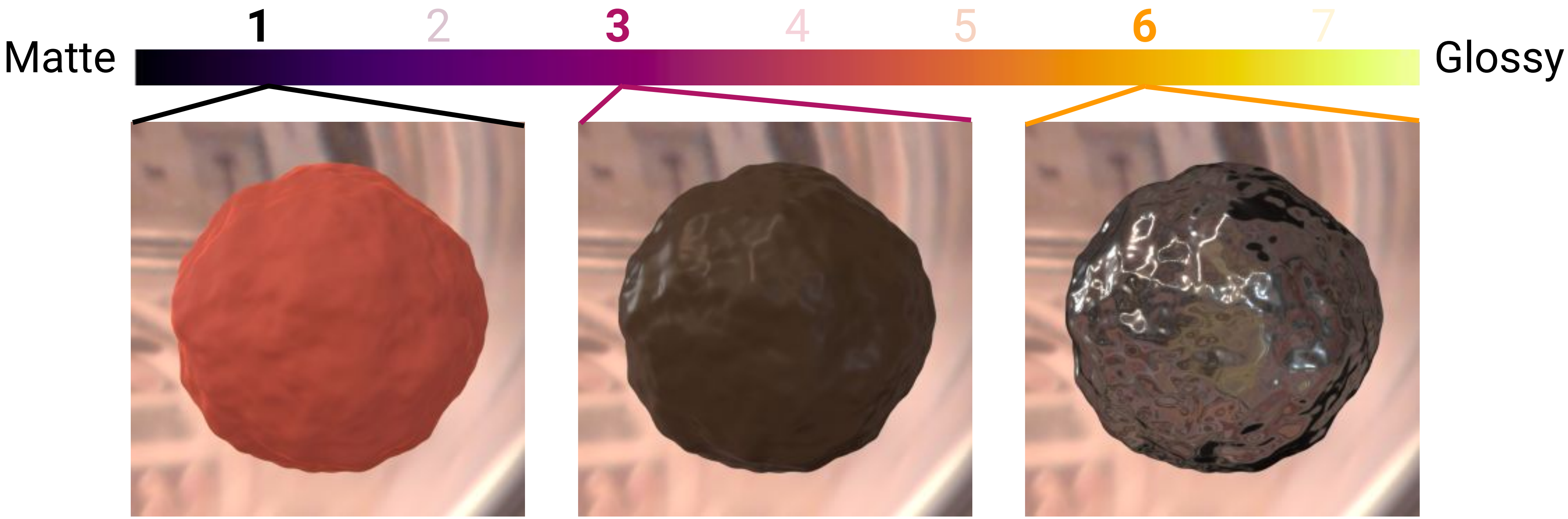
GT	1.00	3.00	6.00
S.100%	2.00	3.87	7.00

Results: Qualitative



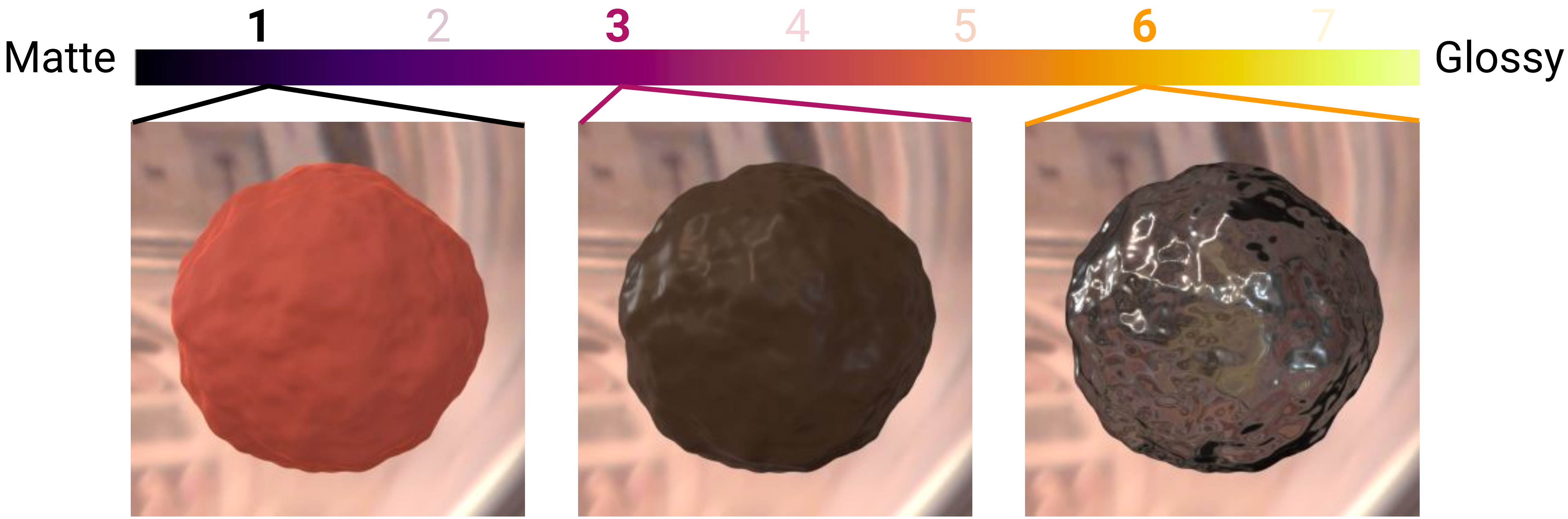
GT	1.00	3.00	6.00
S.100%	2.00	3.87	7.00
S.100% + BSDF	1.00	2.90	7.00

Results: Qualitative



GT	1.00	3.00	6.00
S.100%	2.00	3.87	7.00
S.100% + BSDF	1.00	2.90	7.00
S.20% + BSDF	2.04	2.84	7.00

Results: Qualitative



GT	1.00	3.00	6.00
S.100%	2.00	3.87	7.00
S.100% + BSDF	1.00	2.90	7.00
S.20% + BSDF	2.04	2.84	7.00

Results: Qualitative

GT	1.00	5.00	7.00

Results: Qualitative

GT	1.00	5.00	7.00
S.100%	1.06	5.33	6.96
S.100% + BSDF	1.00	4.73	7.00
S.20% + BSDF	1.89	3.08	7.00

Results: Qualitative

GT	1.00	5.00	7.00
S.100%	1.06	5.33	6.96
S.100% + BSDF	1.00	4.73	7.00
S.20% + BSDF	1.89	3.08	7.00

Results: Consistency

Consistent gloss prediction, with respect to:

- Rotations
- Geometry complexity
- Illumination frequency
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Results: Comparison to SOTA

Gloss predictor		MAE $\downarrow$	Spearman $\uparrow$	Pearson $\uparrow$
	Serrano et al.			
Ours	S.100%+BSDF			
	S.20%+BSDF			

Results: Comparison to SOTA

Gloss predictor		MAE ↓	Spearman ↑	Pearson ↑
Serrano et al.		0.3293		
Ours	S.100%+BSDF			
	S.20%+BSDF			

Results: Comparison to SOTA

Gloss predictor		MAE ↓	Spearman ↑	Pearson ↑
	Serrano et al.	0.3293	0.5662	0.5358
Ours	S.100%+BSDF			
	S.20%+BSDF			

Results: Comparison to SOTA

Gloss predictor		MAE ↓	Spearman ↑	Pearson ↑
	Serrano et al.	0.3293	0.5662	0.5358
Ours	S.100%+BSDF	**0.1207**	**0.8594**	**0.8788**
	S.20%+BSDF	0.1538	0.8366	0.8228

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Less manual annotations

Results: Generalization to Real Photographs

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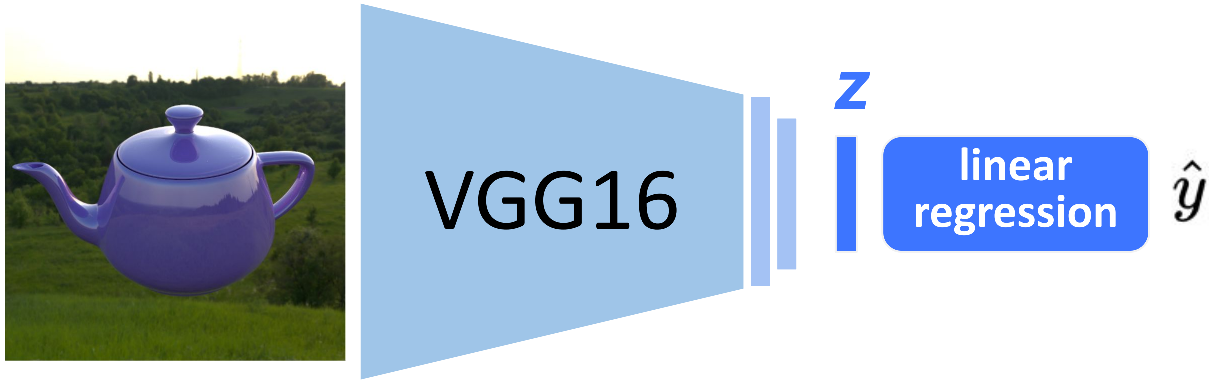
Gloss predictor		MAE ↓	Spearman ↑	Pearson ↑
	Serrano et al.	0.3327	0.4546	0.4266
Ours	S.100%+BSDF	**0.2236**	**0.6625**	**0.6570**
	S.20%+BSDF	0.2386	0.6208	0.6063

Results: Perceptually Meaningful Latent Space



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20 dimensional latent space ***z***

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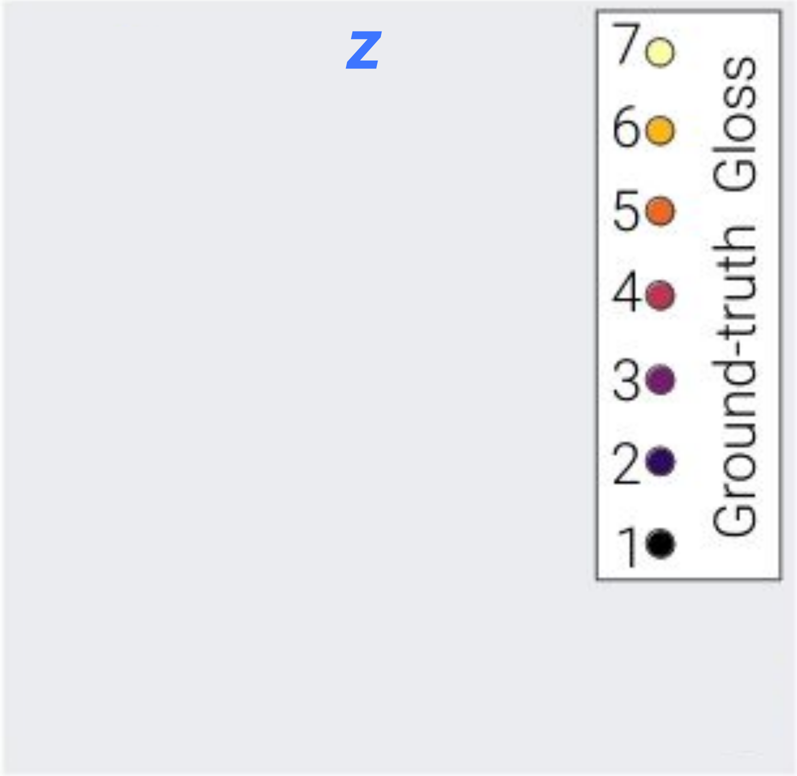
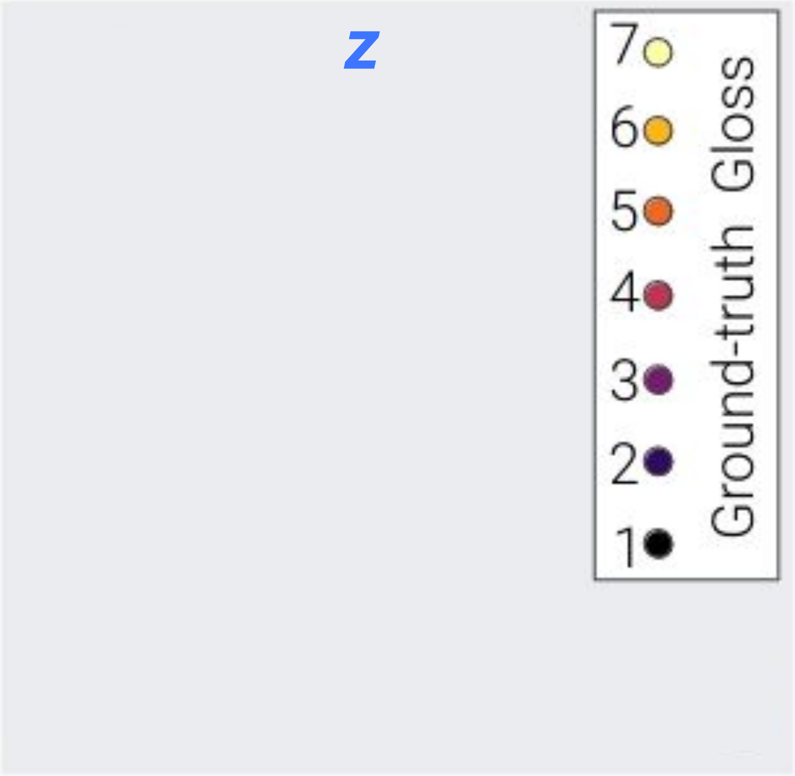


Results: Perceptually Meaningful Latent Space

20 dimensional latent space z



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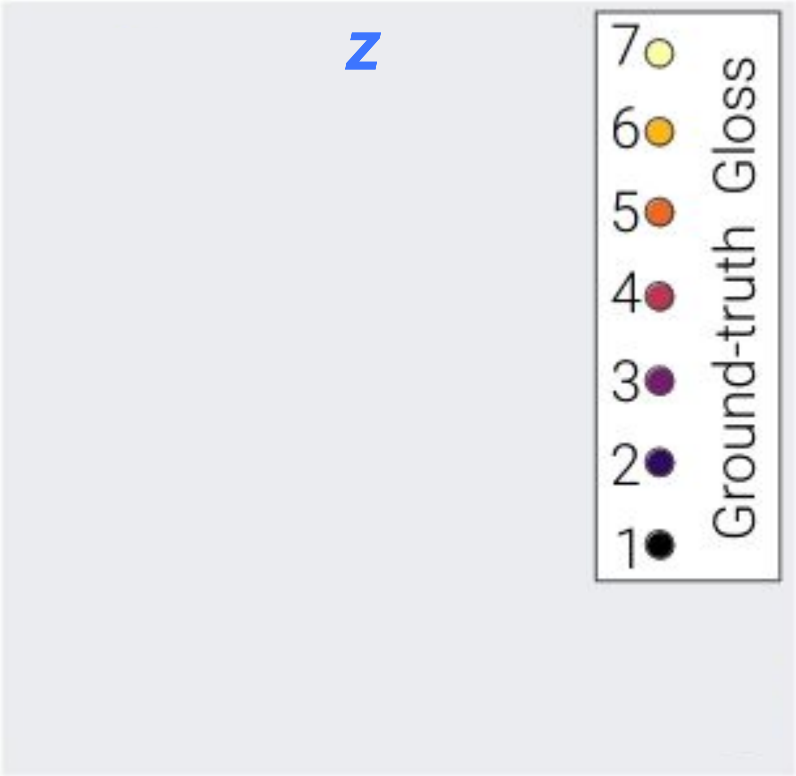

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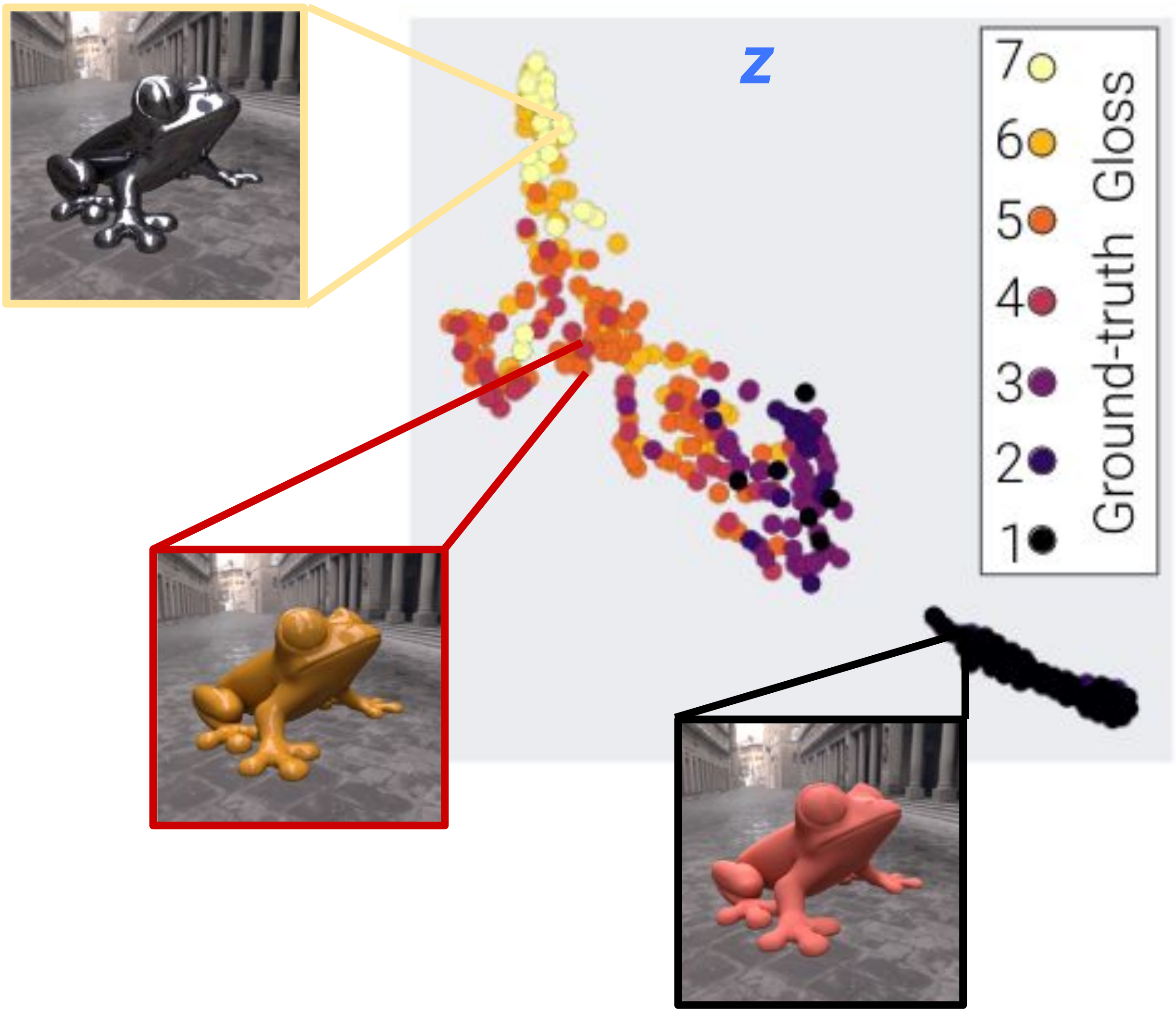

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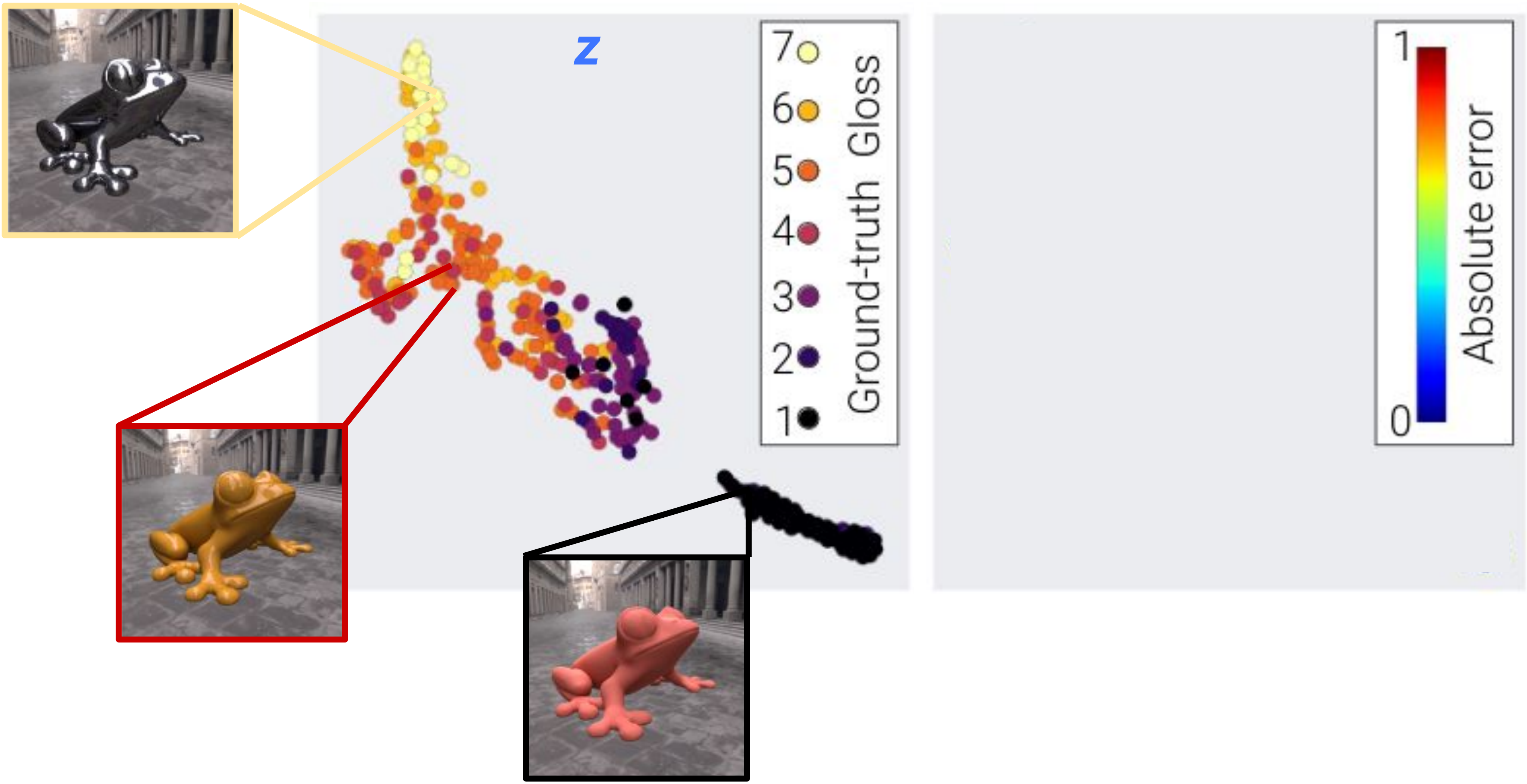

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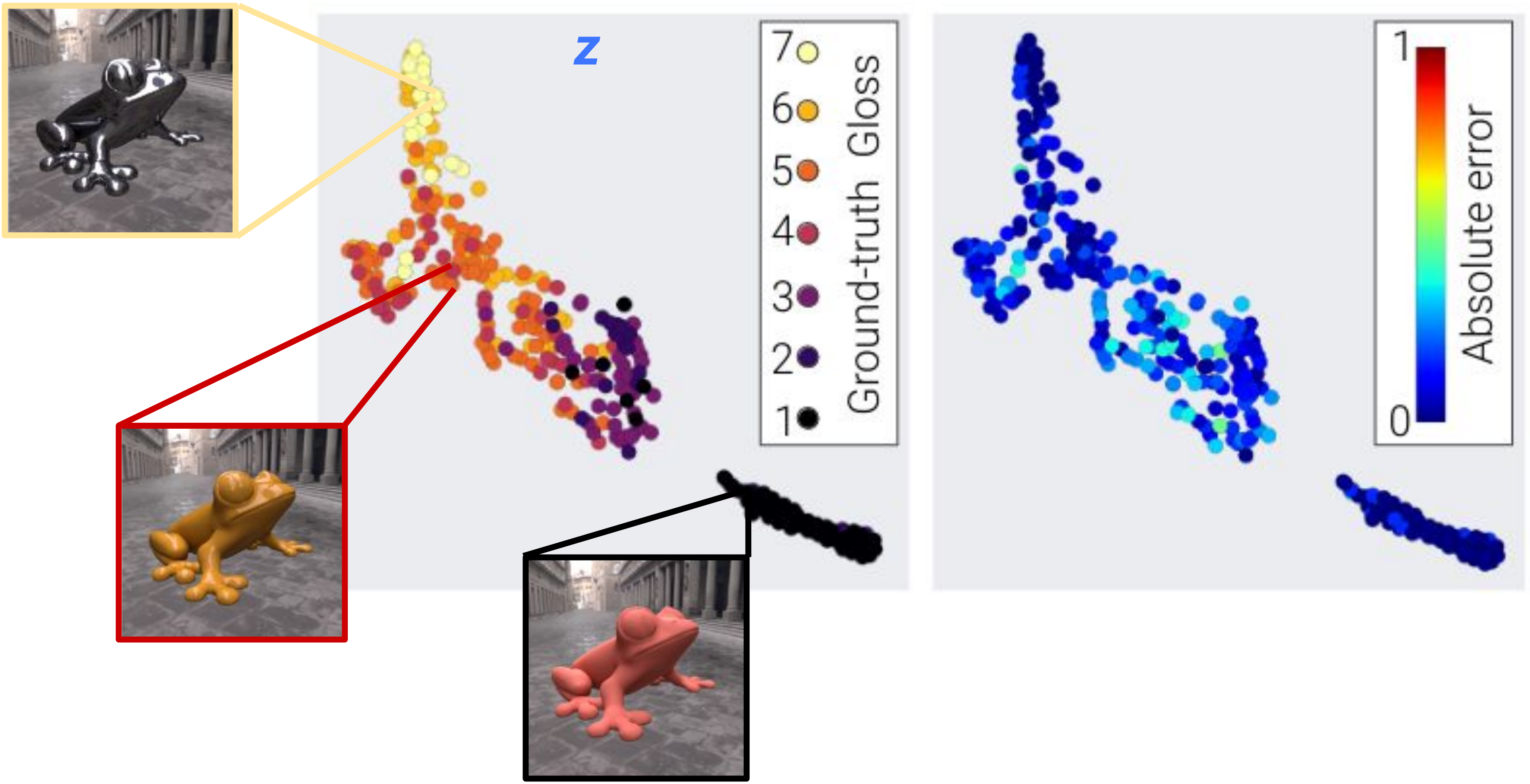

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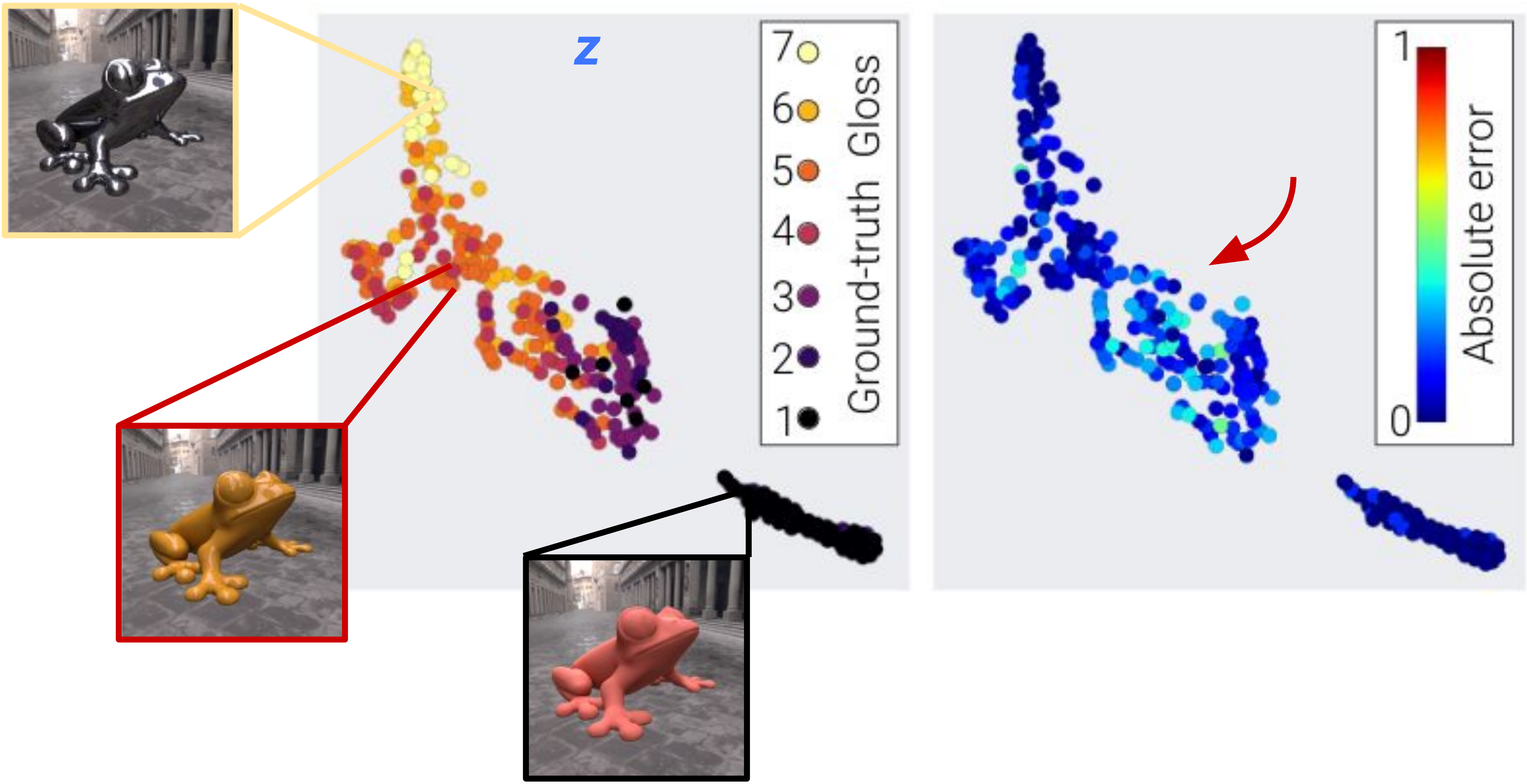

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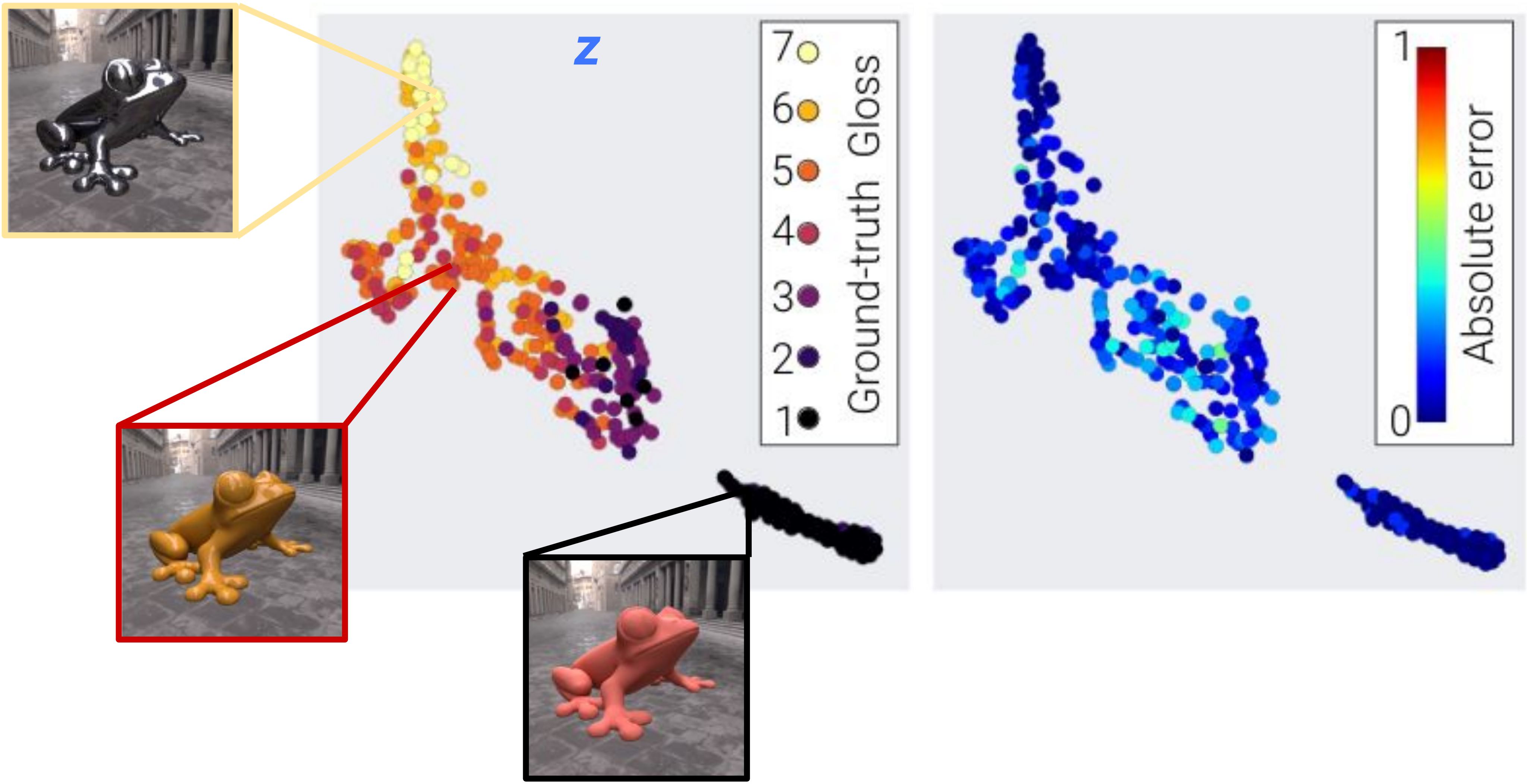

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- Challenging examples: patterned surfaces and sharp shadows

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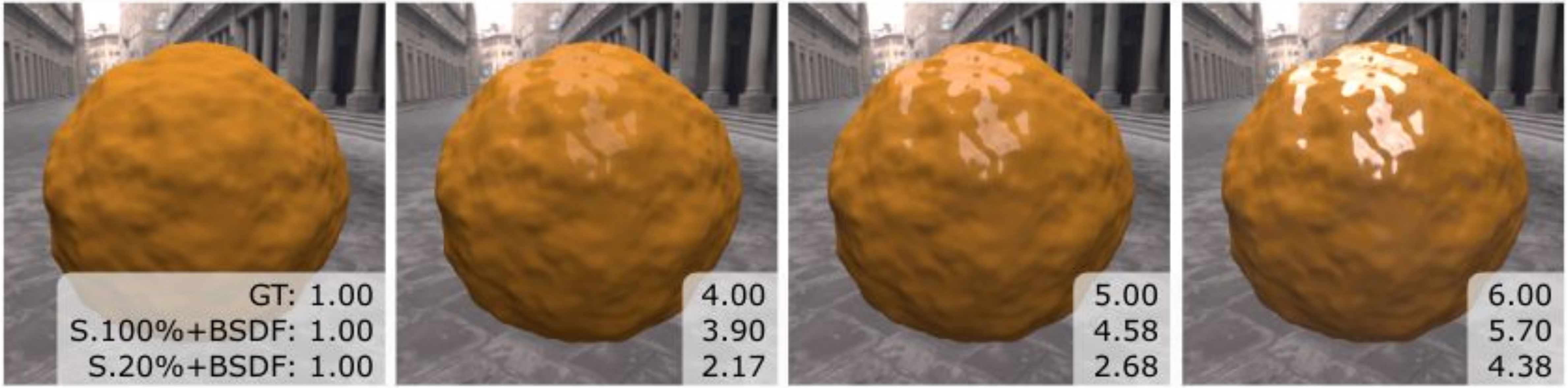

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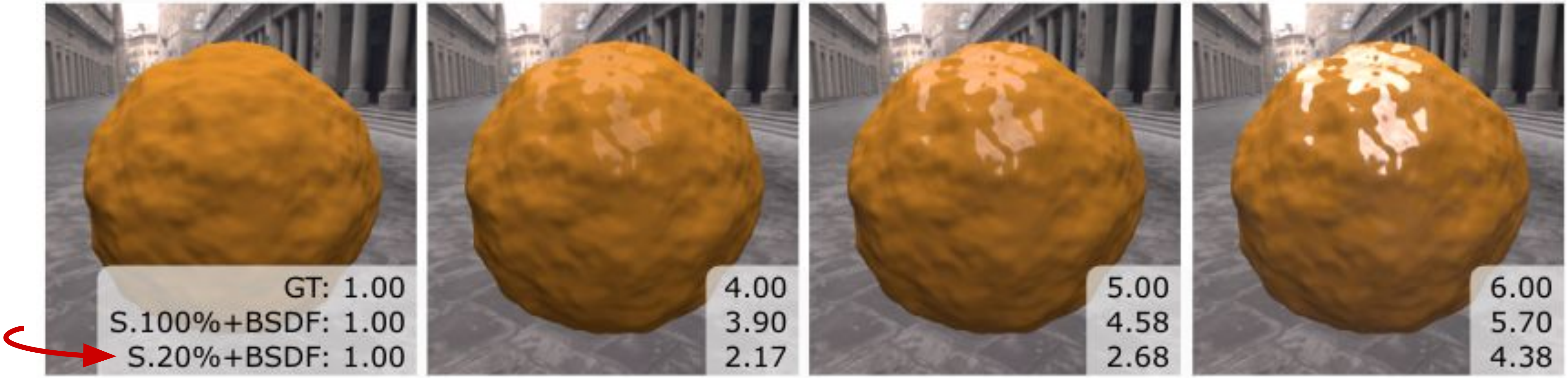

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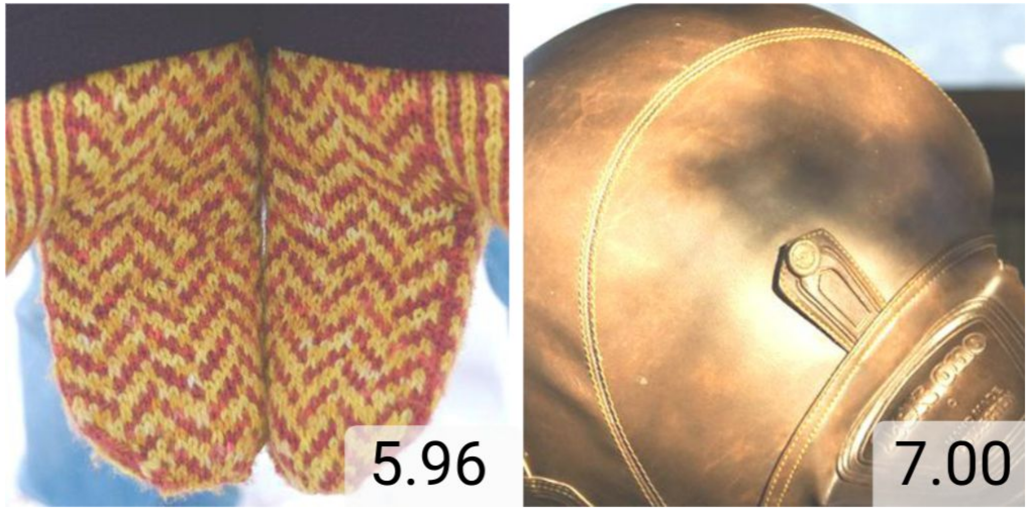
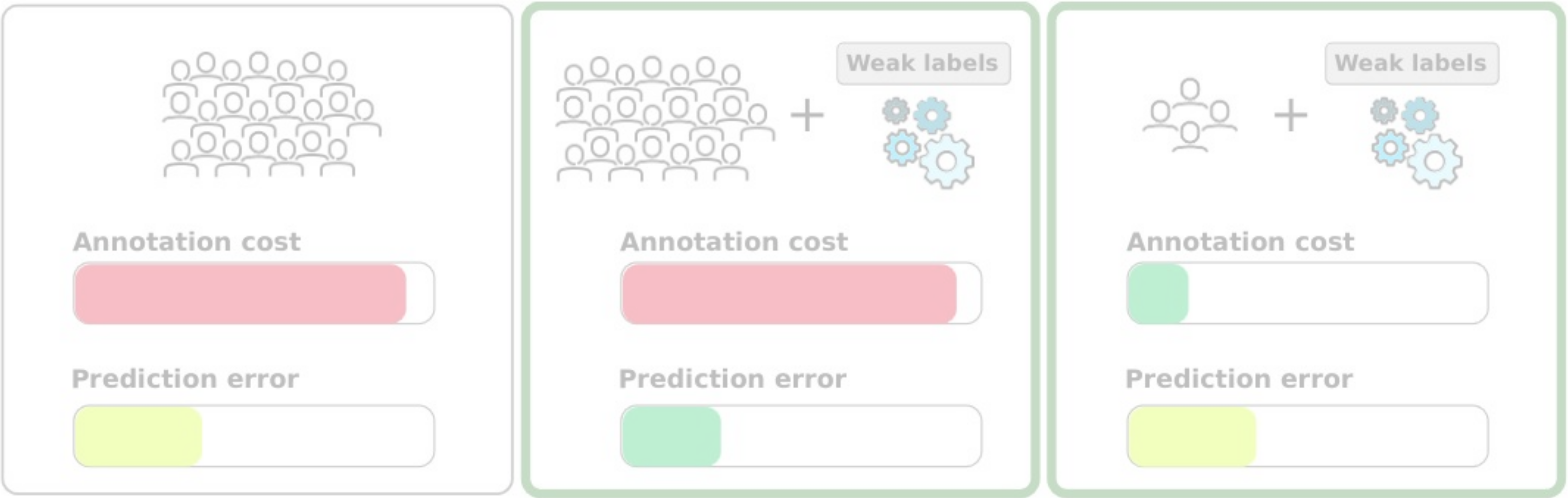


Conclusion

- Weak labels to **reduce manual annotation cost** for perceptual studies
- **State-of-the-art performance** in gloss prediction
- **Consistency**, **generalization** to real photos, and well organized **latent space**



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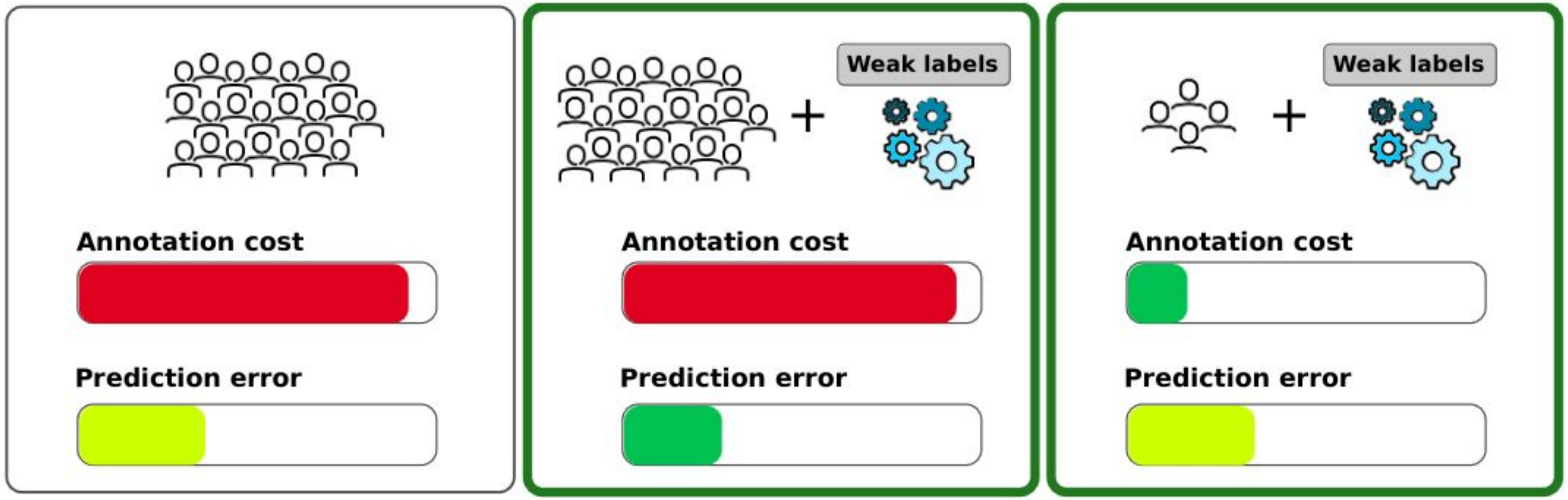

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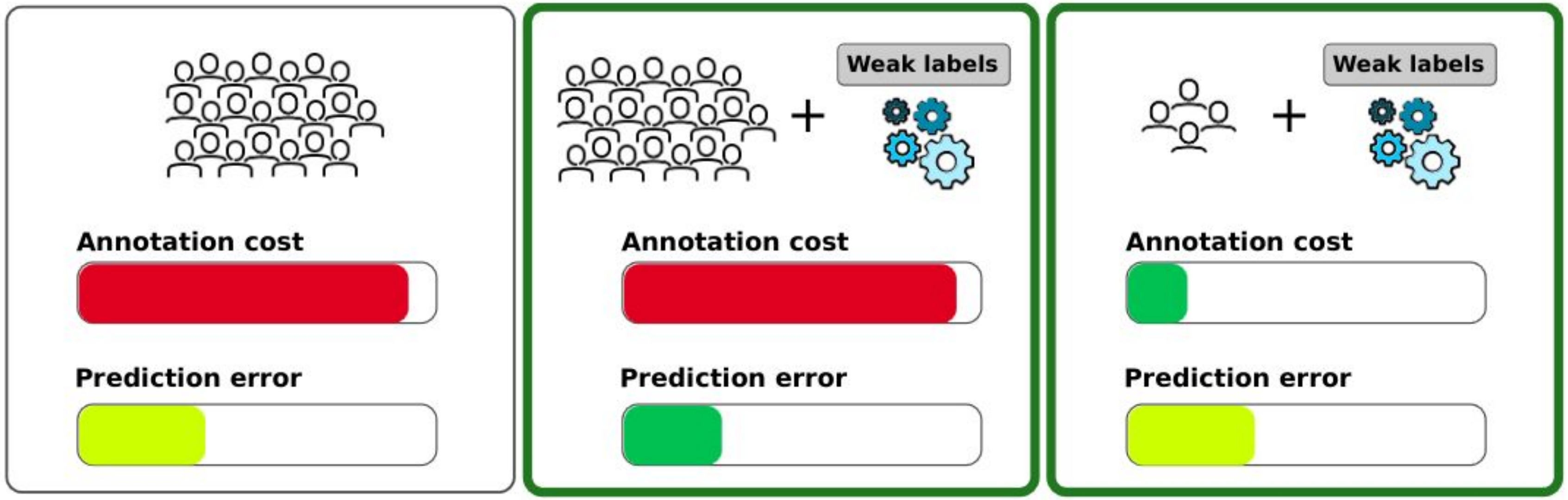

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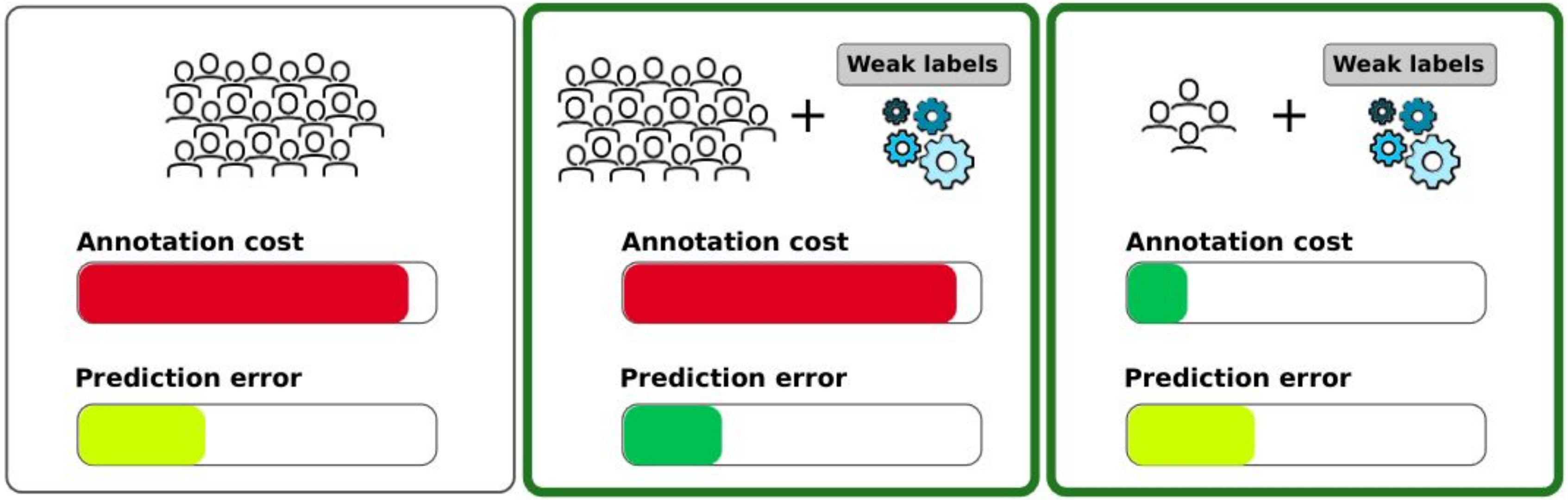

Predicting Perceived Gloss: Do Weak Labels Suffice?

Julia Guerrero-Viu*, J. Daniel Subias*, Ana Serrano, Katherine R. Storrs, Roland W. Fleming, Belen Masia, Diego Gutierrez

EUROGRAPHICS
CONFERENCE 2024

- Weak labels to reduce manual annotation cost for perceptual studies
- State-of-the-art performance in gloss prediction
- Consistency, generalization to real photos, and perceptually meaningful latent space

Code and data:

Contact: juliagviu@unizar.es

Instituto Universitario de Investigación de Ingeniería de Aragón
Universidad Zaragoza
Graphics and Imaging Lab
THE UNIVERSITY OF AUCKLAND NEW ZEALAND
JUSTUS-LIEBIG-UNIVERSITÄT GIESSEN
Center for Mind, Brain and Behavior CMBB