On the effect of age perception biases for real age regression

Julio C. S. Jacques Junior [1,2], Cagri Ozcinar [3], Marina Marjanovic [4], Xavier Baró [1,2], Gholamreza Anbarjafari [5,6], Sergio Escalera [2,7]

[1] Universitat Oberta de Catalunya, Spain, [2] Computer Vision Center, Spain, [3] School of Computer Science and Statistics, Trinity College Dublin, Ireland, [4] Singidunum University, Serbia, [5] University of Tartu, Estonia, [6] Institute of Digital Technologies, Loughborough University London, UK, [7] University of Barcelona, Spain

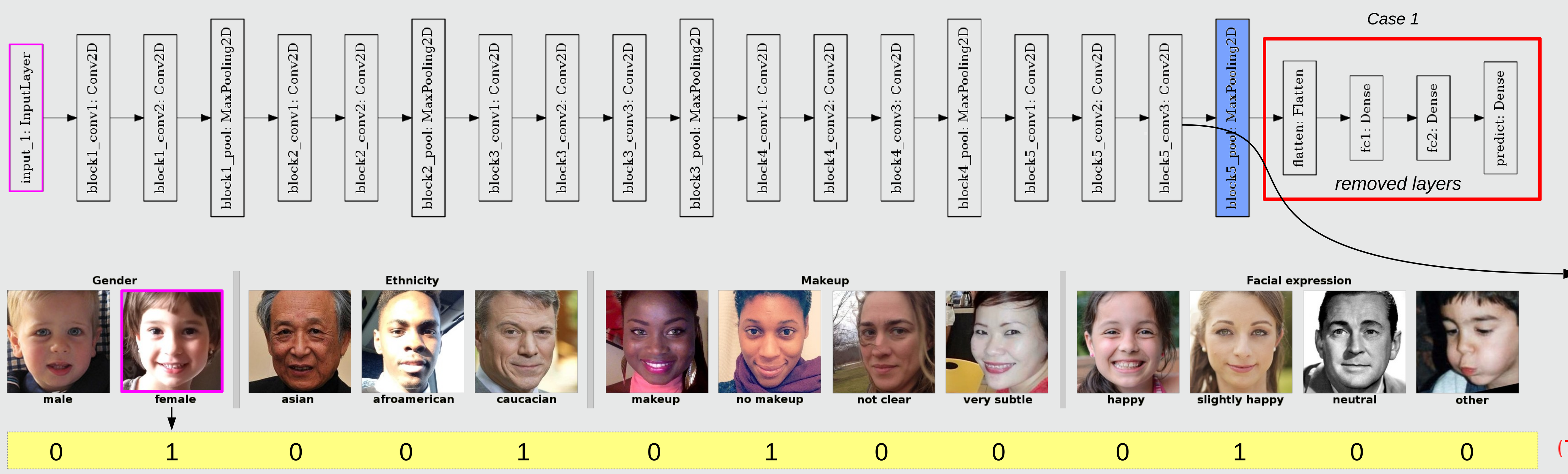
Abstract and Motivation

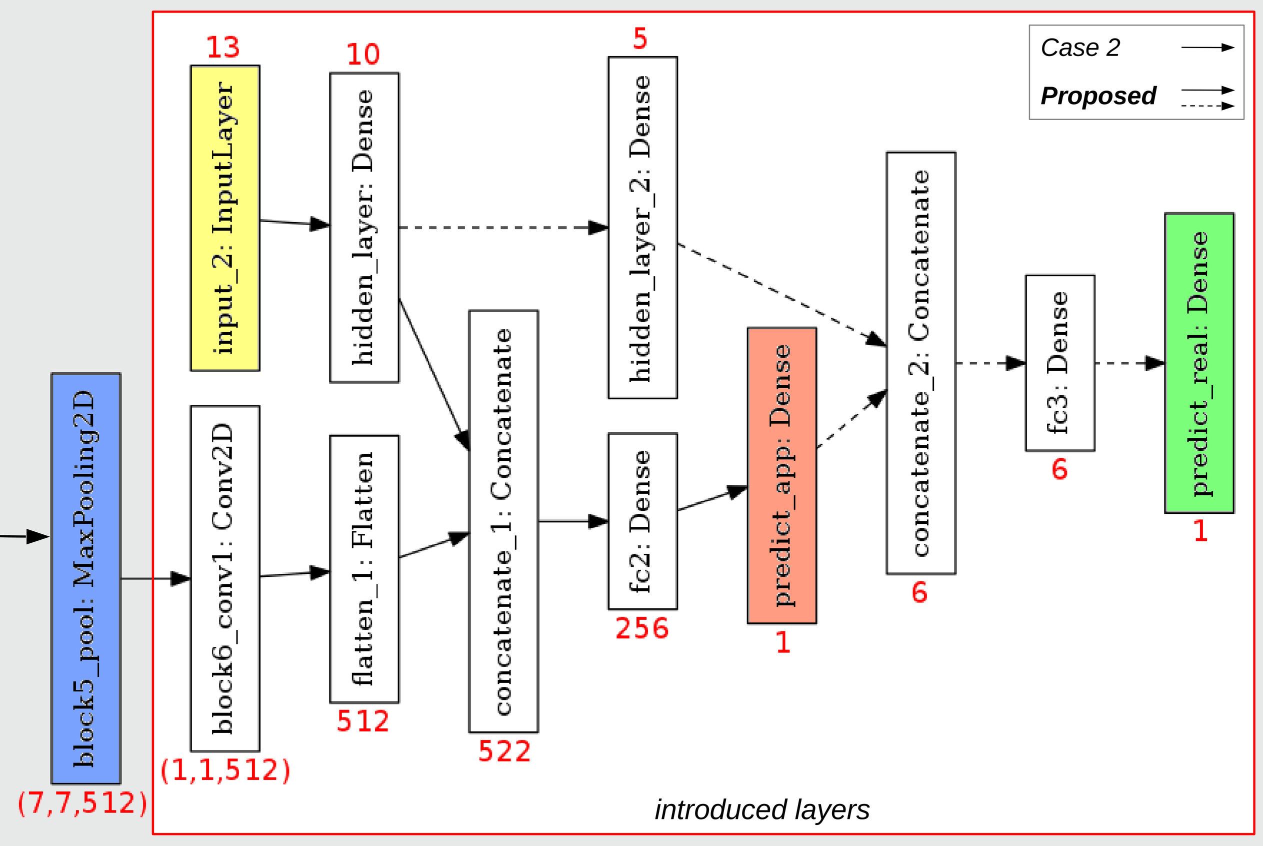
- This work analyses the effect of **gender**, **ethnicity**, **makeup** and **facial expression** as sources of bias to improve apparent age prediction.
- Following recent works [2, 3] where it is shown that **apparent age perception** benefits **real age estimation**, rather than direct real to real age regression, our main contribution is the integration, in an end-to-end architecture, of face attributes for apparent age prediction with an additional loss for real age regression.
- Finally, we present preliminary results and discussion of a **proof of concept application** using the proposed model to regress the apparent age of an individual **based on the gender of an external observer**.

Proposed Model

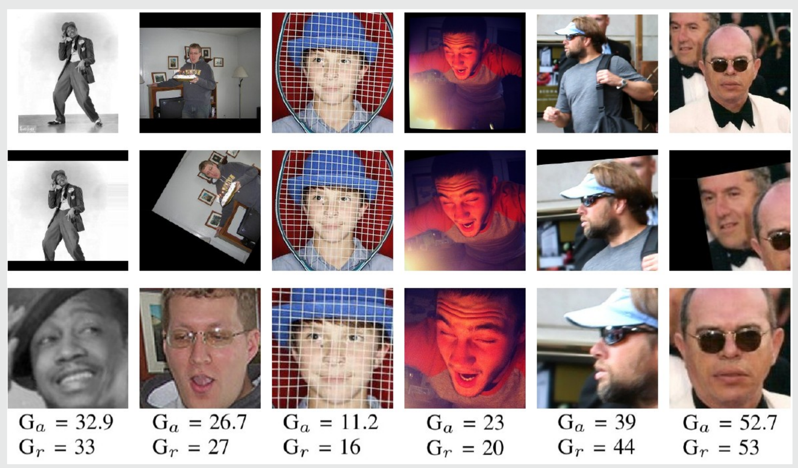
The proposed model combines apparent and real age labels with additional **face attributes** during training. Note that, once the model is trained, it uses neither real nor apparent age labels on the test set.

- To achieve our objectives, we modify the last layers of VGG16, as follows:





Experimental Results



Samples of the **APPA-REAL dataset** [3] (~8K images). *First row:* original images. *Second row:* “cropped faces” (provided with the dataset). *Third row:* cropped faces obtained with [11], used in this work.

With (case 2) / **without** (cases 1 & 2') **attributes**.

Case	Input label	Predict	MAE
1	App	App	7.532
	App	Real	9.199
	Real	Real	10.385
2'	App - att	App	6.228
	App - att	Real	7.517
	Real - att	Real	7.909
2	App + att	App	**6.024**
	App + att	Real	**7.483**
	Real + att	Real	7.782

State-of-the-art comparison.

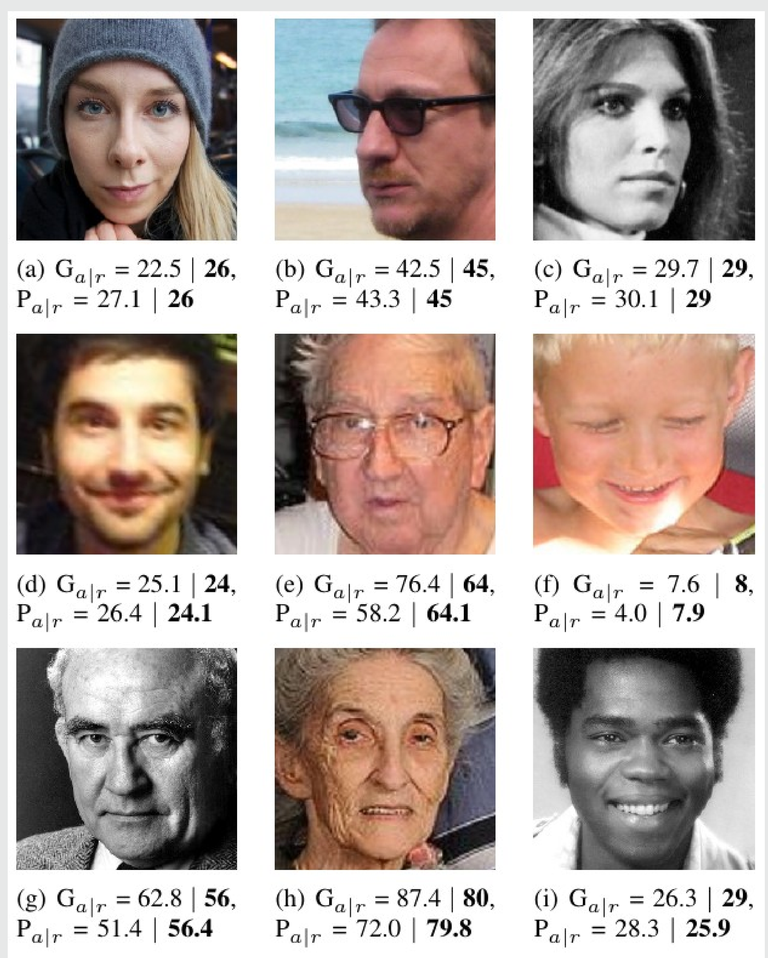
Model	Input label	Predict	MAE
Clapés et al. [2]	App + att	Real	13.577
	Real + att	Real	14.572
Proposed	App + Real + att	App	**6.131**
		Real	**7.356**

Trainable parameters.

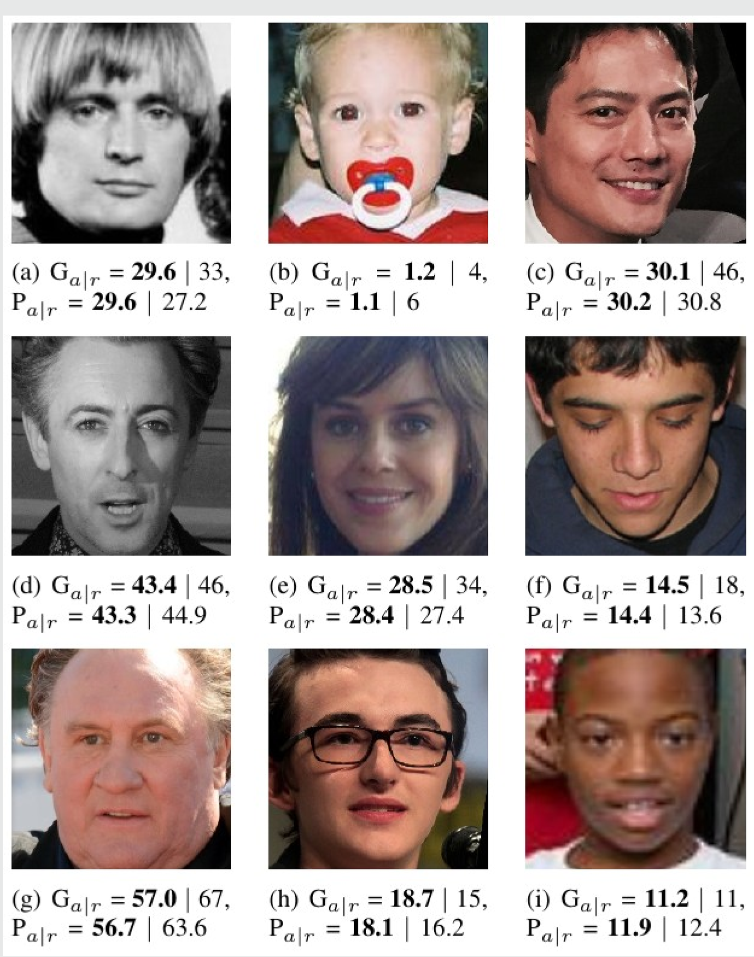
Case 1	134,264,641
Case 2	27,694,541
Proposed	**27,694,645**

Individual analysis of attributes.

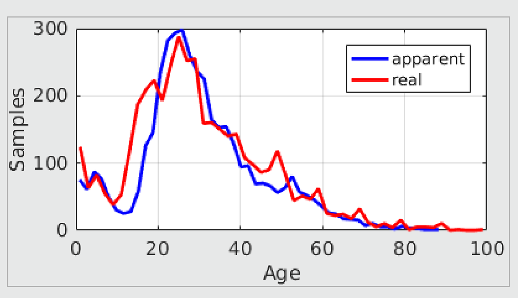
Attribute	Cat.	% Tr.	Real	App
Gender	Male	50.72	**6.55**	6.27
	Female	49.28	8.11	**5.99**
Race	Asian	10.43	**6.59**	5.36
	Caucasian	86.6	7.40	6.21
	Afroamerican	2.97	7.73	**5.30**
Happy	Happy	17.53	7.58	6.11
	Slightly	43.71	7.63	**6.05**
	Neutral	34.67	**6.99**	6.16
	Other	4.09	7.34	6.35
Makeup	Makeup	19.72	7.35	**4.61**
	No make-up	72.33	7.33	6.92
	Not clear	0.98	8.86	5.76
	Very subtle	6.98	**7.20**	6.52



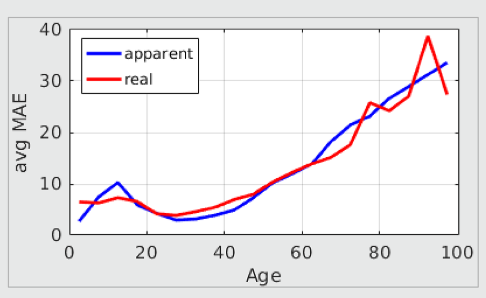
Results based on **real age** estimation error.



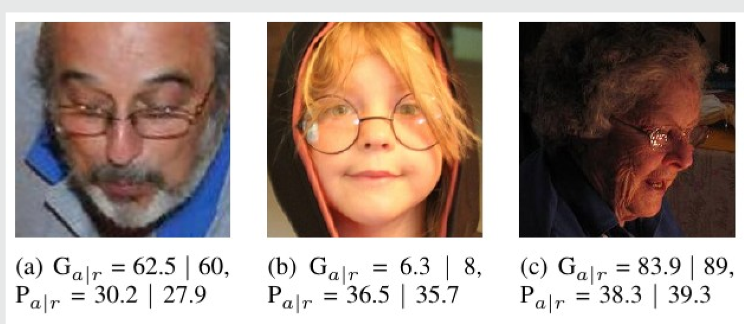
Results based on **apparent age** estimation error.



Age distribution on the train set.



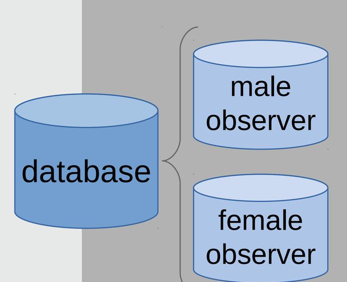
Average error distribution

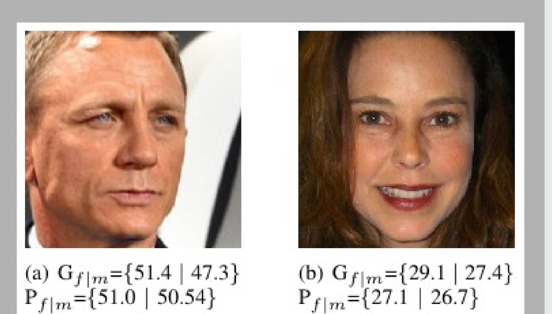


Unsatisfactory results, which may be caused due to partial occlusion, illumination condition, head-pose or even due small number of samples in the train set for those age ranges.

proof of concept application

How a male/female observer will **perceive** your age?





Female observer (MAE) = 9.758
Male observer (MAE) = 9.243

Conclusions

- While the network in its first layers **uses these face attributes as bias to improve apparent age estimation**, the last layers of the network are in charge of doing the opposite, i.e., benefiting from an improved apparent age estimation and face attributes to **unbias** apparent predictions **to regress the real age**.
- Improvements in both apparent and real age estimation can be tackled jointly in an end-to-end fashion when combined with specific attributes people use in everyday life when drawing first impressions about others.
- Future work will include the extension of both amount of data and number of attributes for a deeper analysis of the bias involved in age perception.

[2] A. Clapés, O. Bilici, D. Temirova, E. Avots, G. Anbarjafari, and S. Escalera, **“From apparent to real age: gender, age, ethnic, makeup, and expression bias analysis in real age estimation,”** in IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2018, pp. 2373-2382.

[3] E. Agustsson, R. Timofte, S. Escalera, X. Baro, I. Guyon, and R. Rothe, **“Apparent and real age estimation in still images with deep residual regressors on appa-real database,”** in International Conference on Automatic Face & Gesture Recognition (FG), 2017, pp. 87-94.

[11] K. Zhang, Z. Zhang, Z. Li, and Y. Qiao, **“Joint face detection and alignment using multitask cascaded convolutional networks,”** IEEE Signal Processing Letters, vol. 23, no. 10, pp. 1499-1503, 2016.

code/data