On the Role of Individual Differences in Current Approaches to Computational Image Aesthetics

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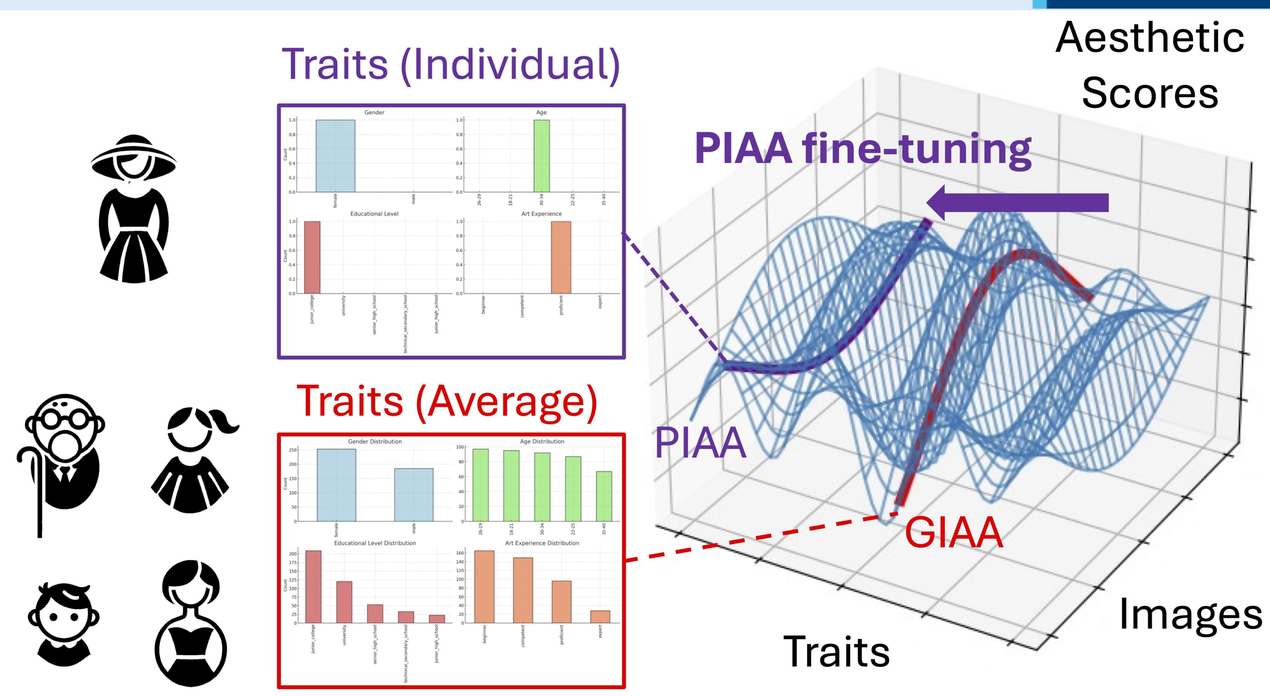
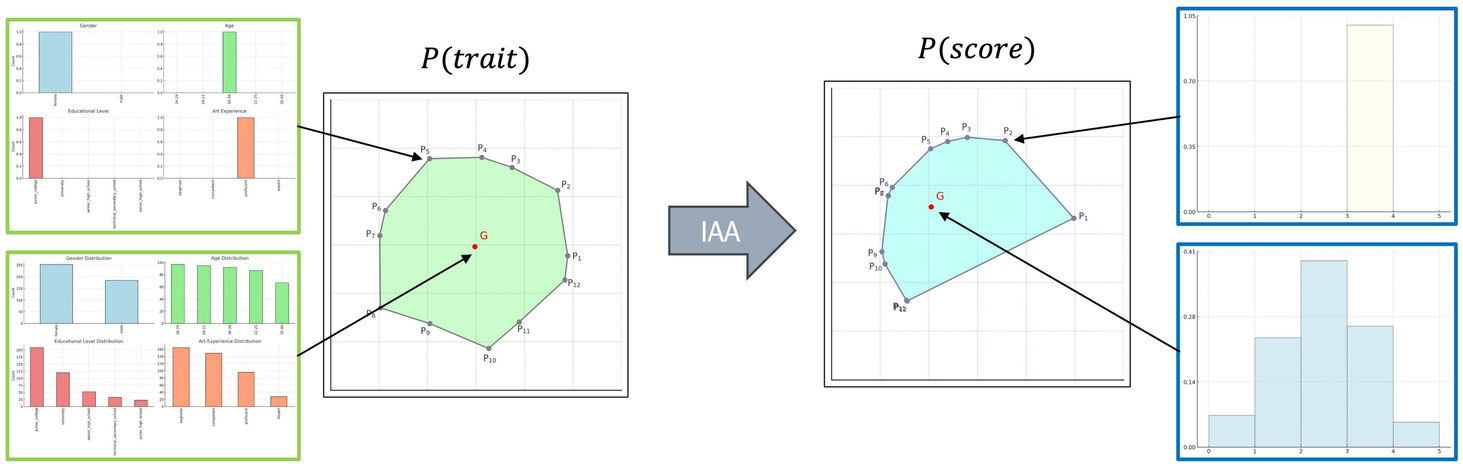
1. Introduction

- Image Aesthetic Assessment (IAA): evaluates how aesthetically pleasing an image is.
- Challenge: image diversity + subjectivity.
- Existing approaches learn IAA by two stages:
  - Generic IAA (GIAA): learns group-level mean aesthetics to address image diversity.
  - Personal IAA (PIAA): fine-tunes on individual data (*i.e.*, transfer learning) to account for subjectivity.



2. Problem

- The current pipeline relies on transfer learning between GIAA and PIAA, but their differences are difficult to interpret since they only appear as parameter shifts during fine-tuning.
- Existing work offers limited insight into the role of group composition—such as demographic factors and group size—and how these factors affect transfer learning.

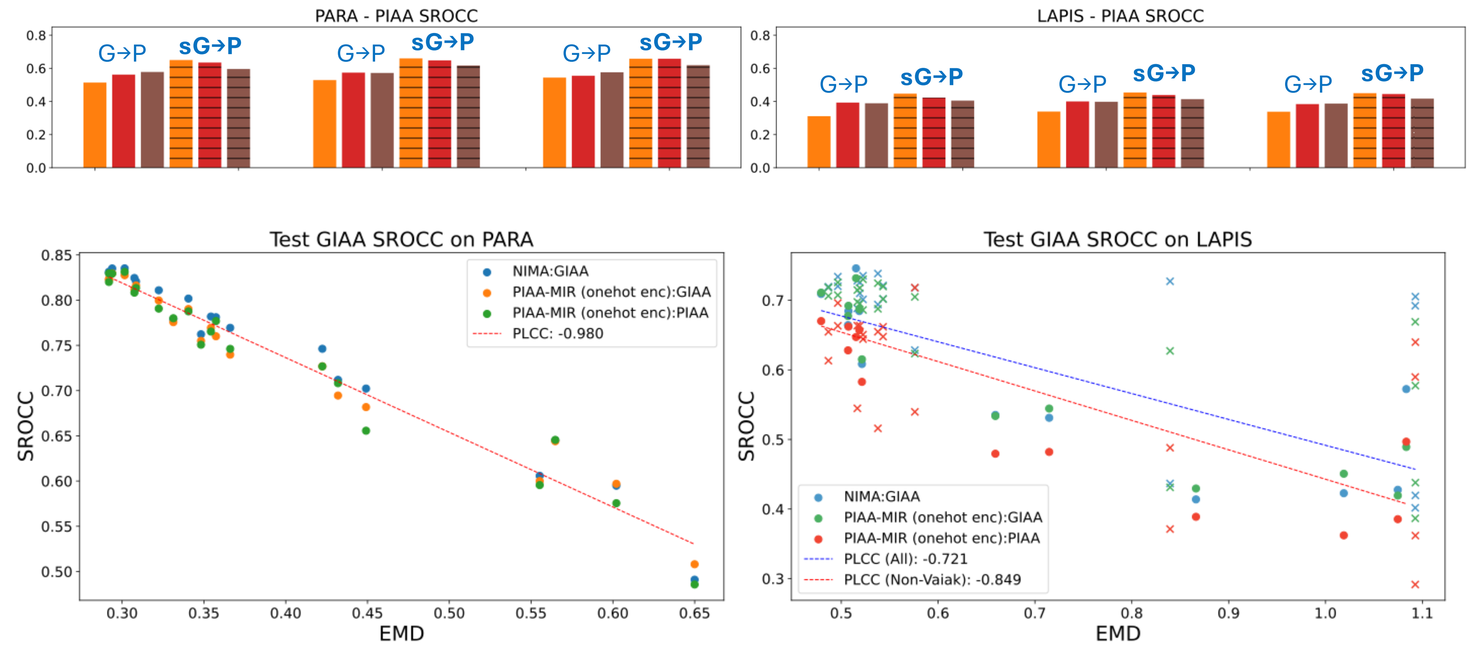


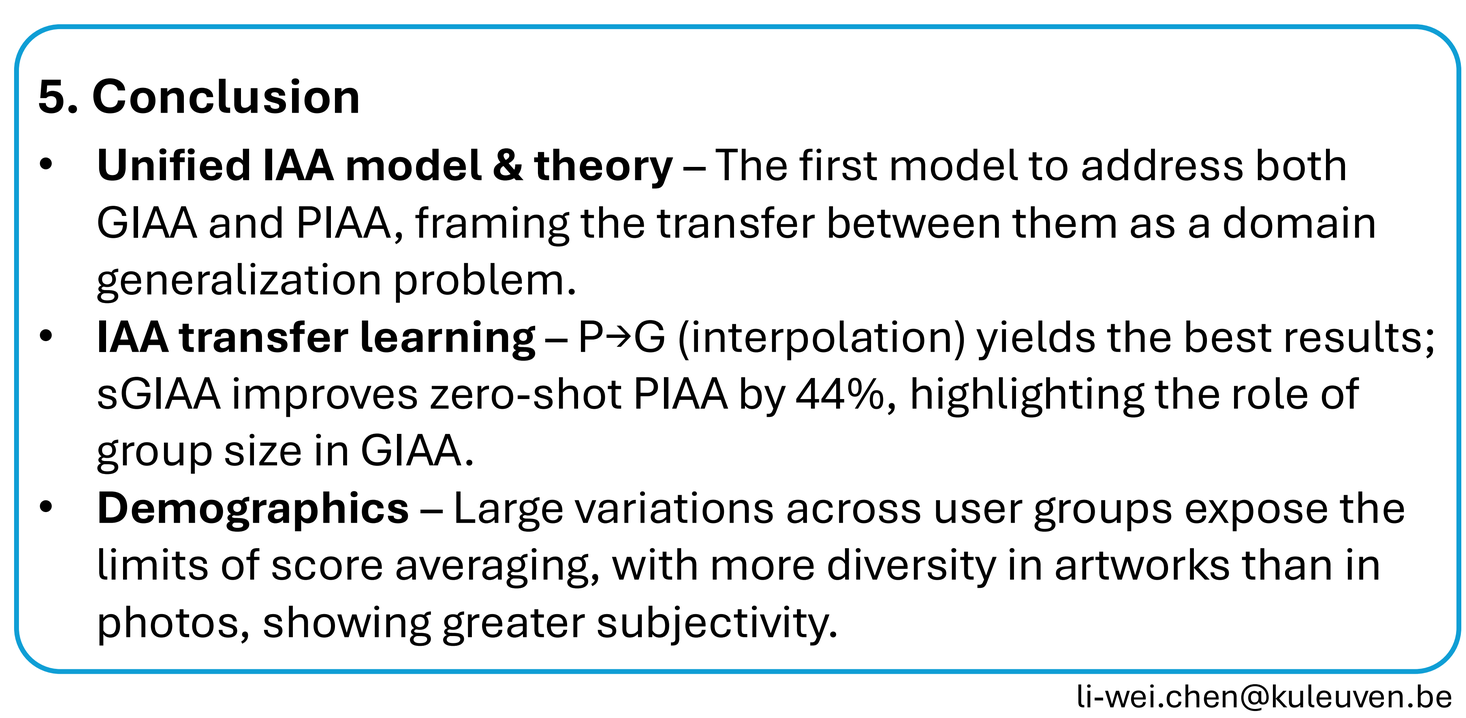
3. Method

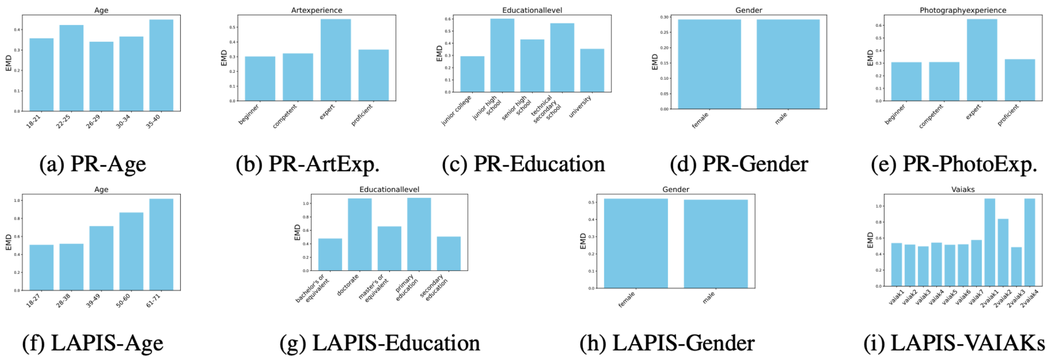
- We propose unified IAA models for both GIAA and PIAA
  - Building on existing SOTA methods, we encode all demographic features and scores as distributions (denoted as 'Onehot enc.' in our results).
  - **This turns the transfer learning into domain generalization.**
    - Interpolation (P→G)
    - Extrapolation (G→P)

4. Experimental Validation

- Dataset
  - PARA (PR): photos
  - LAPIS: artworks
- **Transfer learning between GIAA and PIAA**
  - P→G performs significantly better than G→P, which agrees with our theory.
  - To investigate the effect of group size in G→P, we propose **Sub-sampled GIAA (sGIAA)** to sample group with smaller size. It improves G→P (*i.e.*, zero-shot PIAA) performance by up to 44%.
- **Generalization across demographics**
  - EMD of score distribution highly correlates with the model performance, making it an effective indicator for identifying new users.







5. Conclusion

- **Unified IAA model & theory** – The first model to address both GIAA and PIAA, framing the transfer between them as a domain generalization problem.
- **IAA transfer learning** – P→G (interpolation) yields the best results; sGIAA improves zero-shot PIAA by 44%, highlighting the role of group size in GIAA.
- **Demographics** – Large variations across user groups expose the limits of score averaging, with more diversity in artworks than in photos, showing greater subjectivity.

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