

Colorful Bias

Table of Contents

- [Introduction](#)
- [Setup and Reproduction](#)
- [Literature Review](#)
 - [Race/Ethnicity-Annotated Face Datasets](#)
 - [Image Colorization Research](#)
 - [Bias Metrics](#)
- [Methods](#)
 - [Choosing the Dataset](#)
 - [Sampling Data](#)
 - [Downloading Models](#)
 - [Computing Metrics](#)
 - [Analyzing Colorization](#)
- [Results](#)
 - [Recolorization](#)
 - [Barcharts](#)
 - [Facets](#)
 - [Joyplots](#)
 - [Summary Statistics](#)
 - [Multivariate Mixed-Effects Model](#)
- [Limitations](#)
- [Conclusion](#)
- [References](#)

Introduction

In 2015, Google Photos faced widespread backlash after its [algorithms mislabeled](#) Black people as gorillas [1]. Three years later, the MIT Media Lab found that facial recognition systems had [error rates](#) as high as 34% for darker-skinned women compared to less than 1% for lighter-skinned men [2]. From image classification to facial recognition, computer vision is infamously flawed. In this research project, I investigated how these issues of fairness manifest in the age of generative AI. In particular, I explored the robustness of generative algorithms for image colorization with respect to skin tone bias. To accomplish this, I conducted a survey of race/ethnicity-annotated face datasets, compiled seminal algorithms for image colorization over the years, researched various formulations of bias metrics, and set up a code framework with statistical tests to rigorously compare the performance of coloring procedures. Through the above work, I sought to shed light on the trend in "colorful" bias, or bias in algorithmic colorization of images containing human skin tones, as seen through algorithms over time. Code is available at <https://github.com/drakedu/colorful-bias>.

Setup and Reproduction

This project uses Python 3.11.

1. `git clone https://github.com/drakedu/colorful-bias`
2. `pip install requirements.txt`
3. `python download_data.py`
4. `python sample_data.py`
5. `python explore_data.py`
6. `python download_models.py`
7. `python run_colorization.py`
8. `python compute_metrics.py`
9. `python analyze_colorization.py`

Literature Review

Race/Ethnicity-Annotated Face Datasets

Many race/ethnicity-annotated face datasets have emerged over the years. Some have faced criticism for how their data were provisioned, an issue that has afflicted computer vision and AI more broadly. One such example is MORPH-II, which, as explained in [MORPH-II: Inconsistencies and Cleaning Whitepaper](#), drew from "55,134 mugshots taken between 2003 and late 2007" [3]. Beyond collection, datasets also use different localized conceptions of race/ethnicity, a potentially problematic inconsistency highlighted in [Racial Bias within Face Recognition: A Survey](#) [4] and [One Label, One Billion Faces: Usage and Consistency of Racial Categories in Computer Vision](#) [5]. Still, even if identities could be balanced in a standardized way, [What Should Be Balanced in a "Balanced" Face Recognition Dataset?](#) notes that this does not ensure balance in "other factors known to impact accuracy, such as head pose, brightness, and image quality" [6]. With this context in mind, we provide an overview of a few race/ethnicity-annotated face datasets.

Name	Year	Active	Count	Standardization	Races/Ethnicities
MORPH-II	2006	No	55134	No	Asian, Black, Hispanic, White
Face Place	2008	Yes	235	Yes	Asian, Black, Caucasian, Hispanic, Multiracial

Name	Year	Active	Count	Standardization	Races/Ethnicities
Todorov 13125	2013	Yes	13125	Yes	Asian, Black, White
CFD	2015	Yes	827+	Yes	Asian, Black, Latino, White
RFW	2018	Yes	40607	Yes	African, Asian, Caucasian, Indian
UTKFace	2019	No	20000+	No	Asian, Black, Indian, White
DemogPairs	2019	Yes	10800	Yes	Asian, Black, White
DiveFace	2019	Yes	150000+	Yes	Caucasian, East Asian, Sub-Saharan and South Indian
BFW	2020	No	20000+	Yes	Asian, Black, Indian, White
VMER	2020	No	3000000+	Yes	African American, Asian Indian, Caucasian Latin, East Asian
FDEA	2021	No	157801	Yes	African, Asian, Caucasian
FairFace	2021	Yes	108501	No	Asian, Black, Indian, White
FaceARG	2021	Yes	175000+	Yes	African-American, Asian, Caucasian, Indian
BUPT-BalancedFace	2022	Yes	1300000+	Yes	African, Asian, Caucasian, Indian

Image Colorization Research

Strategies for image colorization have evolved over the years and feature a diversity of AI frameworks as well as user inputs. Some examples of unsupervised methods include focus on random fields [7, 8], stochastic sampling [9], deep neural networks [10, 11, 12, 13, 14], encoders and decoders [15, 16], convolutional neural networks [17, 18, 19, 20], generative adversarial networks [21, 22, 23, 24], instance-aware coloring [25, 26, 27], transformers [28, 29, 30], and transfer learning [31]. Likewise, supervised methods leverage sample scribbles and strokes [32, 33, 34, 35, 36, 37, 38, 39], reference images or patches [40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58], target color palettes and pixels [59, 60, 61, 62], text descriptions [63, 64, 65, 66, 67, 68], and multimodal combinations of these [69, 70, 71, 72]. Here, we provide an in-depth overview of research papers on image colorization.

Title	Year	Author(s)	Supervision	Implementation
Color Transfer between Images	2001	Reinhard et al.	Yes	https://github.com/chia56028/Color-Transfer-between-Images
Transferring Color to Greyscale Images	2002	Welsh et al.	Yes	https://github.com/h-wang94/ImageColorization
Colorization Using Optimization	2004	Levin et al.	Yes	https://github.com/soumik12345/colorization-using-optimization
Colorization by Example	2005	Irony et al.	Yes	None
Fast Image and Video Colorization Using Chrominance Blending	2006	Yatziv & Sapiro	Yes	None
Intrinsic Colorization	2008	Liu et al.	Yes	None
Image Colorization Using Similar Images	2012	Gupta et al.	Yes	None
Image Colorization Using Sparse Representation	2013	Pang et al.	Yes	None
Example-based Image Colorization using Locality Consistent Sparse Representation	2014	Li et al.	Yes	None
Learning Large-Scale Automatic Image Colorization	2015	Deshpande et al.	No	https://github.com/aditya12agd5/iccv15_lscolorization
Palette-based Photo Recoloring	2015	Chang et al.	Yes	https://github.com/b-z/photo_recoloring
Deep Colorization	2016	Cheng et al.	No	None
Colorful Image Colorization	2016	Zhang et al.	No	https://github.com/richzhang/colorization
Let There Be Color	2016	Iizuka et al.	No	https://github.com/satoshiiiizuka/siggraph2016_colorization
Learning Representations for Automatic Colorization	2016	Larsson et al.	No	https://github.com/gustavla/autocolorize
Unsupervised Diverse Colorization via Generative Adversarial Networks	2017	Cao et al.	No	https://github.com/ccyyatnet/COLORGAN
Real-Time User-Guided Image Colorization with Learned Deep Priors	2017	Zhang et al.	Yes	https://github.com/junyanz/interactive-deep-colorization
Probabilistic Image Colorization	2017	Royer et al.	No	https://github.com/ameroyer/PIC

Title	Year	Author(s)	Supervision	Implementation
Outline Colorization through Tandem Adversarial Networks	2017	Frans	Yes	None
Learning Diverse Image Colorization	2017	Deshpande et al.	No	https://github.com/aditya12agd5/divcolor
Image Colorization using CNNs and Inception-ResNet-v2	2017	Baldassarre et al.	No	https://github.com/baldassarreFe/deep-koalarization
Controlling Deep Image Synthesis with Sketch and Color	2017	Sangkloy et al.	Yes	None
Deep Exemplar-Based Colorization	2018	He et al.	Yes	https://github.com/msracver/Deep-Exemplar-based-Colorization
Deep Image Prior	2018	Lempitsky et al.	No	https://github.com/DmitryUlyanov/deep-image-prior
DeOldify	2018	Antic	No	https://github.com/jantic/DeOldify
TextureGAN: Controlling Deep Image Synthesis with Texture Patches	2018	Xian et al.	Yes	https://github.com/janesjanes/Pytorch-TextureGAN
Two-Stage Sketch Colorization	2018	Zhang et al.	Yes	None
Learning to Color from Language	2018	Manjunatha et al.	Yes	https://github.com/superhans/colorfromlanguage
Language-Based Image Editing with Recurrent Attentive Models	2018	Chen et al.	Yes	https://github.com/Jianbo-Lab/LBIE
Structural Consistency and Controllability for Diverse Colorization	2018	Messaoud et al.	No	None
Awesome Image Colorization	2018	Mo et al.	Yes	https://github.com/MarkMoHR/Awesome-Image-Colorization
Coloring with Words: Guiding Image Colorization Through Text-based Palette Generation	2018	Bahng et al.	Yes	https://github.com/awesome-davian/Text2Colors/
Pixelated Semantic Colorization	2019	Zhao et al.	No	None
Fully Automatic Video Colorization with Self-Regularization and Diversity	2019	Lei & Chen	No	https://github.com/ChenyangLEI/automatic-video-colorization
A Superpixel-Based Variational Model for Image Colorization	2019	Fang et al.	Yes	None
Adversarial Colorization Of Icons Based On Structure And Color Conditions	2019	Sun et al.	Yes	https://github.com/jxcodetw/Adversarial-Colorization-Of-Icons-Based-On-Structure-And-Color-Conditions
Automatic Example-Based Image Colorization Using Location-Aware Cross-Scale Matching	2019	Li et al.	Yes	None
Coloring With Limited Data: Few-Shot Colorization via Memory Augmented Networks	2019	Yoo et al.	No	https://github.com/dongheehand/MemoPainter-PyTorch
ChromaGAN: Adversarial Picture Colorization with Semantic Class Distribution	2020	Vitoria et al.	No	https://github.com/pvitoria/ChromaGAN
Instance-Aware Image Colorization	2020	Su et al.	No	https://github.com/ericsujw/InstColorization
Reference-Based Sketch Image Colorization using Augmented-Self Reference and Dense Semantic Correspondence	2020	Lee et al.	Yes	None
Stylization-Based Architecture for Fast Deep Exemplar Colorization	2020	Xu et al.	Yes	https://github.com/xuzhongyou/Colorization
Image Colorization: A Survey and Dataset	2020	Anwar et al.	No	https://github.com/saeed-anwar/ColorSurvey
Gray2ColorNet: Transfer More Colors from Reference Image	2020	Lu et al.	Yes	https://github.com/CV-xueba/Gray2ColorNet
Colorization Transformer	2021	Kumar et al.	No	https://github.com/google-research/google-research/tree/master/coltran
Colorizing Old Images Learning from Modern Historical Movies	2021	Jin et al.	No	https://github.com/BestiVictory/HistoryNet

Title	Year	Author(s)	Supervision	Implementation
Yes, "Attention Is All You Need", for Exemplar based Colorization	2021	Yin et al.	Yes	None
User-Guided Line Art Flat Filling with Split Filling Mechanism	2021	Zhang et al.	Yes	https://github.com/Ilyasviel/SplitFilling
Towards Vivid and Diverse Image Colorization with Generative Color Prior	2021	Wu et al.	No	https://github.com/ToTheBeginning/GCP-Colorization
Dual Color Space Guided Sketch Colorization	2021	Dou et al.	Yes	None
Globally and Locally Semantic Colorization via Exemplar-Based Broad-GAN	2021	Li et al.	Yes	None
Deep Edge-Aware Interactive Colorization against Color-Bleeding Effects	2021	Kim et al.	Yes	https://github.com/niceDuckgu/CDR
Bridging the Domain Gap towards Generalization in Automatic Colorization	2022	Lee et al.	No	https://github.com/Lhyejin/DG-Colorization
ColorFormer: Image Colorization via Color Memory assisted Hybrid-attention Transformer	2022	Ji et al.	No	https://github.com/jixiaozhong/ColorFormer
BigColor: Colorization using a Generative Color Prior for Natural Images	2022	Kim et al.	No	https://github.com/KIMGEONUNG/BigColor
Semantic-Sparse Colorization Network for Deep Exemplar-based Colorization	2022	Bai et al.	Yes	https://github.com/bbaaii/SSC-Net
Lightweight Deep Exemplar Colorization via Semantic Attention-Guided Laplacian Pyramid	2022	Zou et al.	Yes	None
UniColor: A Unified Framework for Multi-Modal Colorization with Transformer	2022	Huang et al.	No	https://github.com/luckyhzt/unicolor
Unsupervised Deep Exemplar Colorization via Pyramid Dual Non-Local Attention	2022	Wang et al.	Yes	https://github.com/wd1511/PDNLNA-Net
DDColor: Towards Photo-Realistic Image Colorization via Dual Decoders	2023	Kang et al.	No	https://github.com/piddnad/DDColor
Improved Diffusion-based Image Colorization via Piggybacked Models	2023	Liu et al.	No	https://github.com/hyliu/piggyback-color
Two-Step Training: Adjustable Sketch Colourization via Reference Image and Text Tag	2023	Yan et al.	Yes	https://github.com/tellurion-kanata/sketch_colorizer
Diffusing Colors: Image Colorization with Text Guided Diffusion	2023	Zabari et al.	Yes	None
Region Assisted Sketch Colorization	2023	Wang et al.	Yes	None
L-Colns: Language-based Colorization with Instance Awareness	2023	Chang et al.	Yes	https://github.com/changzheng123/L-Colns
iColoriT: Towards Propagating Local Hint to the Right Region in Interactive Colorization by Leveraging Vision Transformer	2023	Yun et al.	Yes	https://github.com/pmh9960/iColoriT
Adding Conditional Control to Text-to-Image Diffusion Models	2023	Zhang et al.	Yes	https://github.com/Ilyasviel/ControlNet
L-CAD: Language-based Colorization with Any-level Descriptions using Diffusion Priors	2023	Chang et al.	Yes	https://github.com/changzheng123/L-CAD
Automatic Controllable Colorization via Imagination	2024	Cong et al.	No	https://github.com/xy-cong/imagine-colorization
Control Color: Multimodal Diffusion-based Interactive Image Colorization	2024	Liang et al.	Yes	None
Versatile Vision Foundation Model for Image and Video Colorization	2024	Bozic et al.	Yes	None

Bias Metrics

Various conceptualizations of bias have emerged in the image colorization space. Broadly, they include absolute metrics based on geometry, perceptual metrics based on non-uniformities in human color vision, and semantic metrics measuring how well the colorization preserves the semantic meaning of the image. Metrics can further be divided into those requiring a reference image and those that are automatic based on deep learning methods as explained in [Comparison](#)

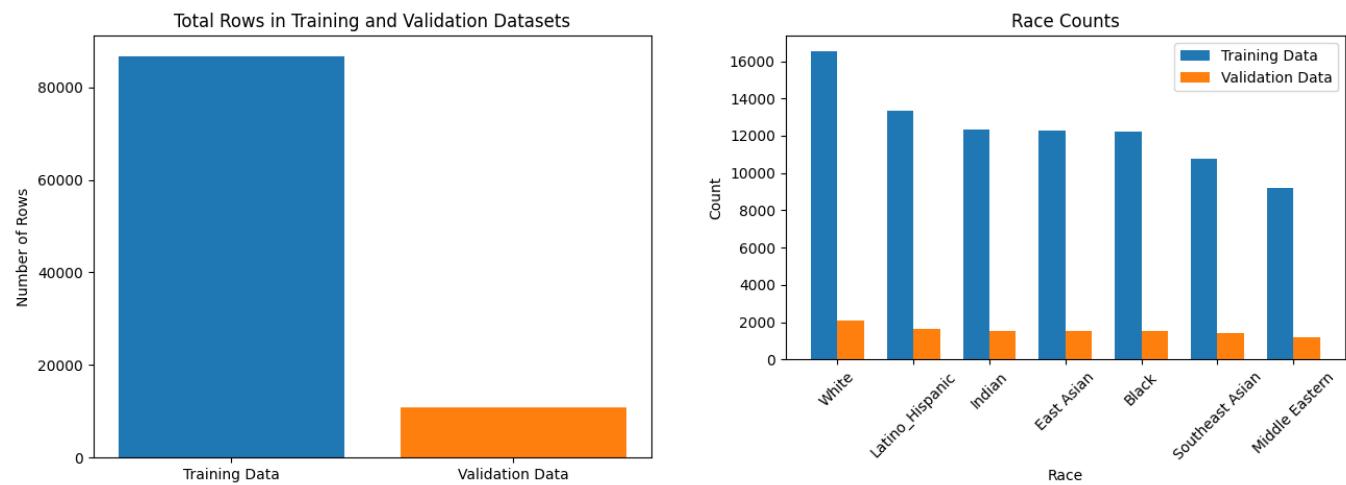
of Metrics for Colorized Image Quality Evaluation [73]. As of December 2024, the two leading Python libraries for image quality assessment (IQA) include PyTorch Toolbox for Image Quality Assessment (PIQA) and PyTorch Image Quality (PIQ). Here, we provide a sampling of bias metrics over the years.

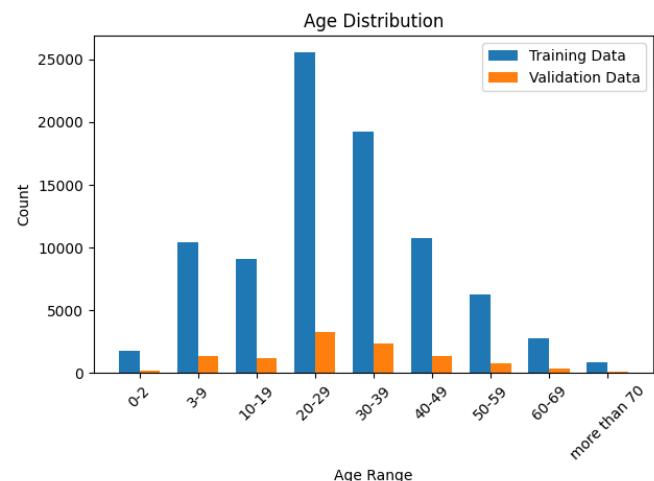
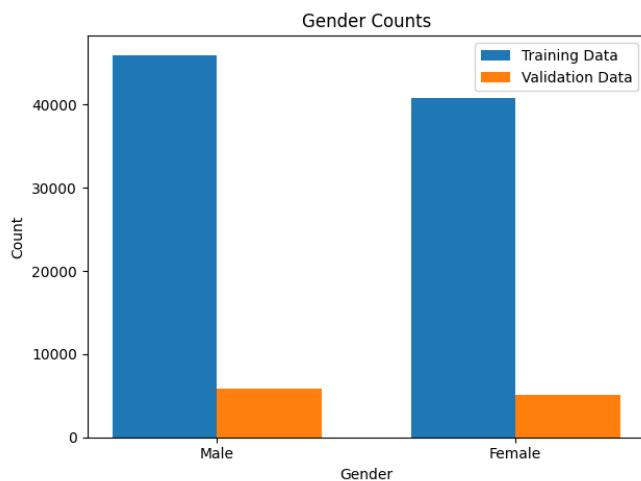
Metric	Year	Type	Reference
Mean Squared Error (MSE)	-	Absolute	Yes
Mean Absolute Error (MAE)	-	Absolute	Yes
Peak Signal-to-Noise Ratio (PSNR)	-	Absolute	Yes
Kullback-Leibler Divergence (KL)	1951	Absolute	Yes
Earth Mover's Distance (EMD)	1989	Absolute	Yes
CIEDE2000	2001	Perceptual	Yes
Universal Image Quality Index (UIQI)	2002	Absolute	Yes
Structural Similarity Index Measure (SSIM)	2004	Perceptual	Yes
Visual Information Fidelity (VIF)	2006	Absolute	Yes
Feature Similarity Index Measure (FSIM)	2011	Perceptual	Yes
Naturalness Image Quality Evaluator (NIQE)	2012	Perceptual	No
Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE)	2012	Perceptual	No
Gradient Magnitude Similarity Deviation (GMSD)	2013	Absolute	Yes
Learned Perceptual Image Patch Similarity (LPIPS)	2018	Semantic	Yes
Neural Image Assessment (NIMA)	2018	Perceptual	No
Deep Bilinear Convolutional Neural Network (DBCNN)	2020	Perceptual	No
Multi-Scale Image Quality Transformer (MUSIQ)	2021	Perceptual	No

Methods

Choosing the Dataset

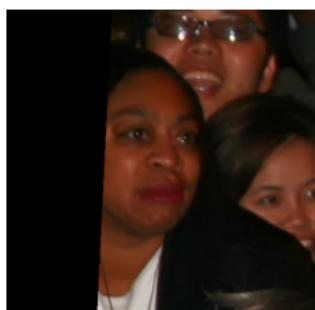
For this research project, [FairFace](#) was employed as the source of race/ethnicity-annotated facial images [74]. This was because FairFace provides wide demographic coverage, including 9 distinct age groups, 7 race/ethnicity categories, and 2 gender groups, for 126 demographic subgroups. Additionally, the dataset is large enough that each individual age-gender-race subgroup contains at least 22 unique images, facilitating statistical analyses. Lastly, FairFace is openly accessible and does not require specific permissions, thereby facilitating the reproducibility and extension of this research project. Below, we display the results of [explore_data.py](#). We can see that the dataset is somewhat imbalanced by all of age, race, and gender and that the smallest age-gender-race subgroup has 22 images.





Gender	Race	0-2	10-19	20-29	3-9	30-39	40-49	50-59	60-69	More than 70
Female	Black	91.0	850.0	1769.0	842.0	1323.0	682.0	371.0	165.0	44.0
Female	East Asian	146.0	632.0	2902.0	675.0	1115.0	348.0	186.0	94.0	43.0
Female	Indian	78.0	890.0	1704.0	695.0	1164.0	659.0	388.0	224.0	107.0
Female	Latino_Hispanic	107.0	918.0	2004.0	837.0	1375.0	832.0	426.0	161.0	55.0
Female	Middle Eastern	28.0	343.0	1041.0	248.0	616.0	327.0	155.0	67.0	22.0
Female	Southeast Asian	76.0	718.0	1871.0	702.0	916.0	412.0	258.0	136.0	94.0
Female	White	166.0	646.0	2972.0	640.0	1911.0	814.0	410.0	193.0	74.0
Male	Black	188.0	668.0	1402.0	1230.0	1296.0	777.0	393.0	114.0	28.0
Male	East Asian	262.0	544.0	1863.0	1061.0	1267.0	591.0	338.0	176.0	44.0
Male	Indian	91.0	639.0	1373.0	835.0	1607.0	976.0	596.0	233.0	60.0
Male	Latino_Hispanic	82.0	691.0	1527.0	752.0	1557.0	1125.0	698.0	194.0	26.0
Male	Middle Eastern	106.0	392.0	1282.0	473.0	1782.0	1190.0	682.0	368.0	94.0
Male	Southeast Asian	138.0	670.0	1639.0	821.0	1093.0	646.0	358.0	171.0	76.0
Male	White	233.0	502.0	2249.0	597.0	2228.0	1365.0	969.0	483.0	75.0

Black Female



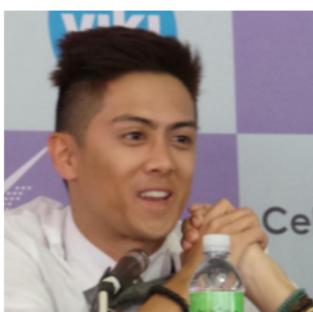
Black Male



East Asian Female



East Asian Male



Indian Female



Indian Male

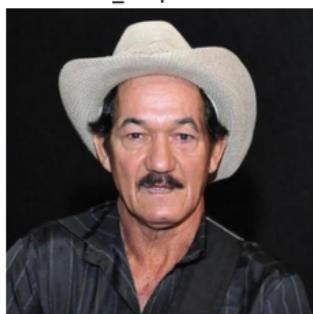




Latino_Hispanic Female



Latino_Hispanic Male



Middle Eastern Female



Middle Eastern Male



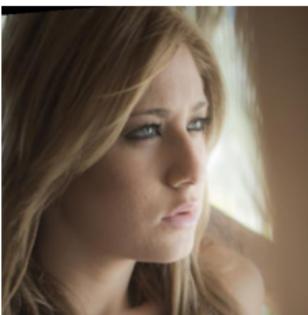
Southeast Asian Female



Southeast Asian Male



White Female



White Male



Sampling Data

To facilitate consistency and comparability across demographic subgroups, we randomly sampled 22 images from each of the 126 demographic categories as defined by unique combinations of age, race/ethnicity, and gender, for a total of 2772 ground-truth images. By setting a baseline per subgroup, we ensured that every group was represented with an equal amount of data, mitigating potential issues arising from imbalanced class sizes.

Downloading Models

While many colorization models have been proposed over the years, a sizeable proportion of them lack open-source implementations. For this research project, we spent 30 minutes attempting to set up each of 37 different models, of which 5 were successfully integrated. These included [Color Transfer between Images](#) [40], [Colorful Image Colorization](#) [17], [Real-Time User-Guided Image Colorization with Learned Deep Priors](#) [18], [DeOldify](#) [75], and [DDColor: Towards Photo-Realistic Image Colorization via Dual Decoders](#) [16]. Due to time constraints, 9 other models received no attempt. Issues included datasets and pre-trained models no longer being publicly available, deprecated packages no longer being offered by channels such as Conda, stringent GPU requirements, macOS incompatibilities with LuaJIT and Caffe, intractable user input requirements, and domain limitations.

Computing Metrics

To determine quality of image recolorization, we leveraged the PyTorch Toolbox for Image Quality Assessment due to its support of a wide-range of seminal metrics and ease of use. Out of the 38 metrics supported by the library, we were able to compute 28 of them for each of the 13860 image recolorings across the 5 models, possibly largely by the help of 6 additional computers in Lamont Library and the blessing of library staff. Q-Align, AHIQ, TReS, MANIQA, ILNIQE, HyperIQA, BRISQUE, NRQM, and PI were projected to take 10 days, 5 days, 4 days, 3 days, 1 day, 16 hours, 15 hours, 7 hours, and 6 hours, respectively, while FID lacked a default image dataset fallback. All 28 metrics taking at most around 6 hours were successfully computed.

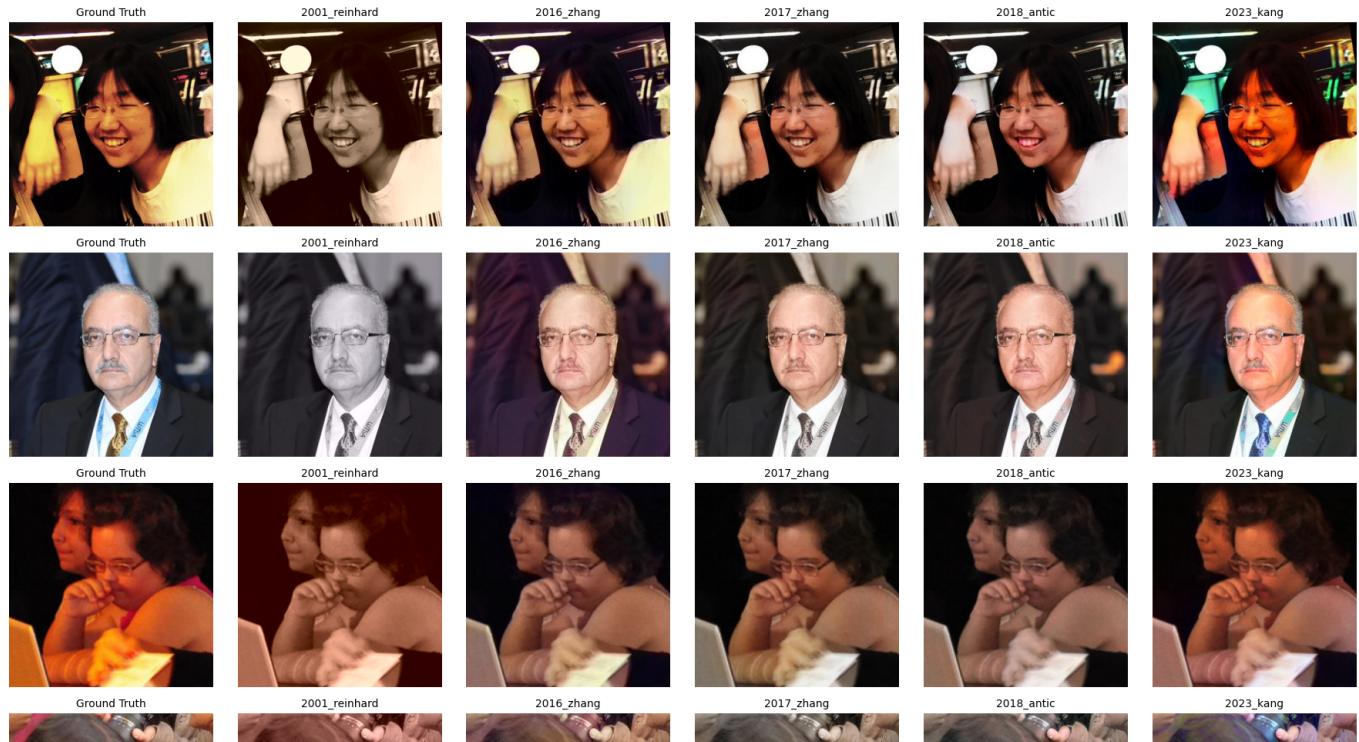
Analyzing Colorization

After computing metrics between ground-truth images and reconstructions, we first explored differences across groups using joyplots, facets, and CI-annotated barcharts. Next, we computed summary statistics for every age-gender-race-model combination, inclusive of an [All](#) keyword, to cover varying aggregations. We then tackled the central question of how demographic disparities in reconstructions differ by colorization algorithm by designing a multivariate mixed-effects model, as it offered a comprehensive, nuanced, and statistically principled framework for our research aims. We recognized that each grayscale image was processed by multiple recolorization models, leading to repeated measures per subject. Leveraging a mixed-effects model naturally accommodated this structure by including random intercepts to capture the inherent variability between subjects, as opposed to treating all observations as independent. This ensured that inference about fixed effects such as the influence of model, race, and their interaction was not confounded by unmodeled differences among images. Additionally, we chose a multivariate approach as we computed 28 different metrics of reconstruction quality, and analyzing these metrics separately would ignore their potentially informative correlations, an idea rooted in both their known explicit relationships as well as possible latent ones. Thus, by including all metrics in a single joint model, this allowed us to determine how disparities manifest through multiple dimensions of quality. Initially, as one might, we sought to look at the within-subject effect of models; the between-subject effects of age, gender, and race; and all interaction terms between these. However, due to computing constraints, we ended up focusing on model, race, and their interaction. Additionally, we tried to fit a multivariate mixed-effects model with all 28 metrics. However, this exhausted the \$50 in cloud compute purchased for the research project as the fitting became increasingly intractable over a span of a few days. As such, for the response variable, I ended up choosing a random 3-sized subset of the 28 metrics in conversation with Jay Pratap. For our normal priors on [mu_subject](#) and [beta](#), we chose standard normals inline with common defaults in hierarchical models as they are neither too tight nor too loose and offer enough flexibility for the data to influence the posterior estimates. Similarly, we set [eta=2](#) for our Lewandowski-Kurowicka-Joe prior to gently shrink correlations toward zero without overly constraining them. Lastly, we had [Exponential\(1.0\)](#) for [sd_dist](#) to favor smaller standard deviations but still allow for larger values if warranted by the data.

Results

Recolorization

Each of the 5 models was able to colorize every one of the 2772 ground truth images over the span of 2 days. Here we have a grid of recolored images from each model displayed against the ground truth, with one sample from each of the 14 race-gender groupings. Differences in the colorization results across the models are clearly visible.

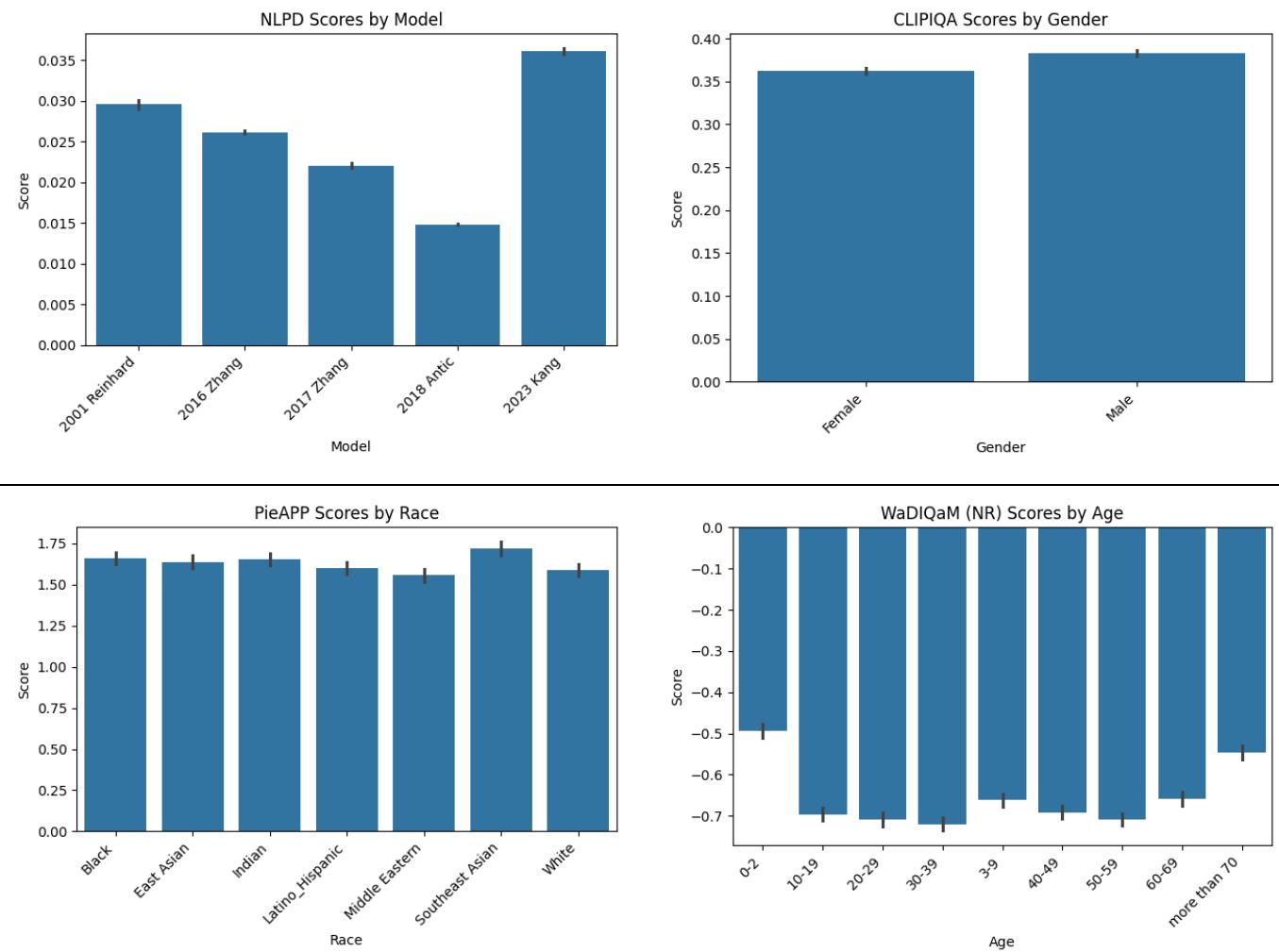






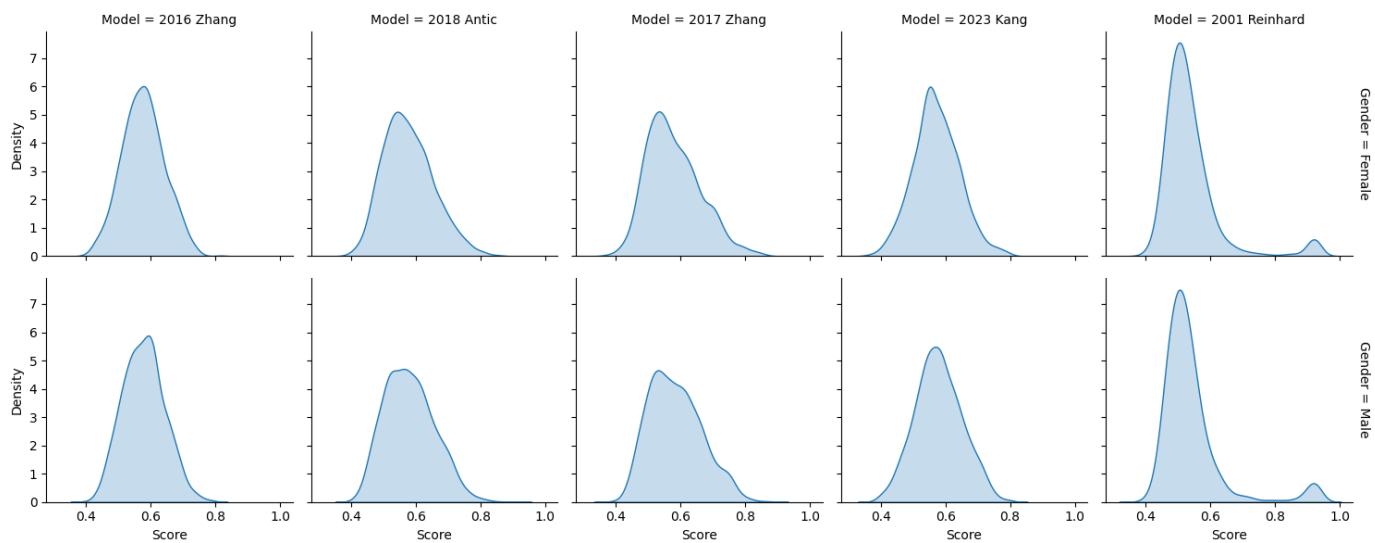
Barcharts

For each metric, we created CI-annotated barcharts to visualize average scores when stratifying by 4 factors: age, gender, race, and model. Here, we look at a subset of results. For NLPD, we very clearly see differences in scores across models. Interestingly, the most recent model of 2023 Kang performs worst on average, as lower scores are better for this metric. For CLIPQA, we see a difference in performance by gender, with images of male subjects having better reconstructions by this metric than female subjects. For PieAPP, we see differences in performance by race, with images of White and Middle Eastern subjects having the best reconstruction scores. Lastly, for no-reference WaDIQaM, we can see noticeable differences in scores across ages, with subjects up to 2 years old or above 70 scoring highest on reconstruction.



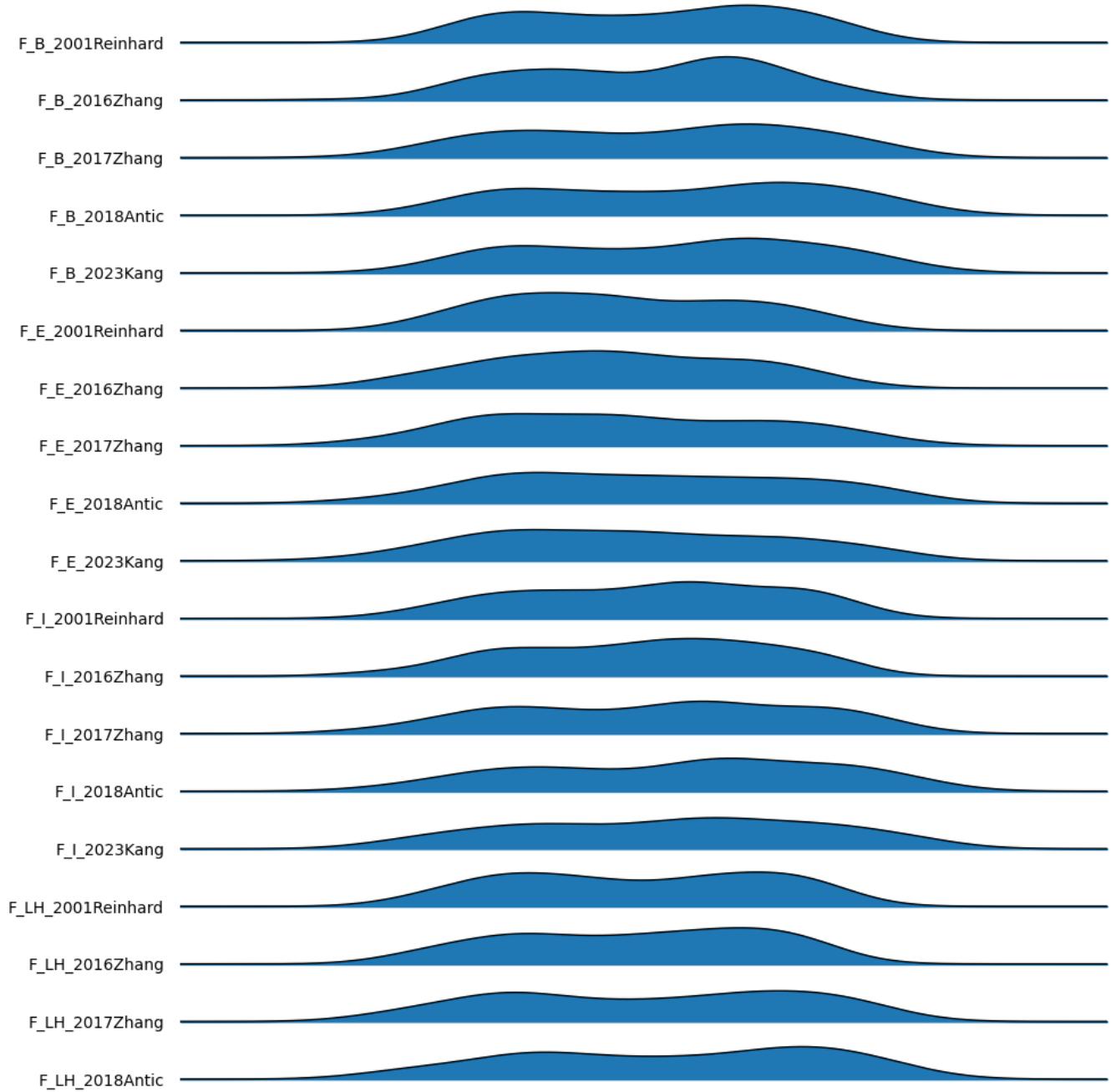
Facets

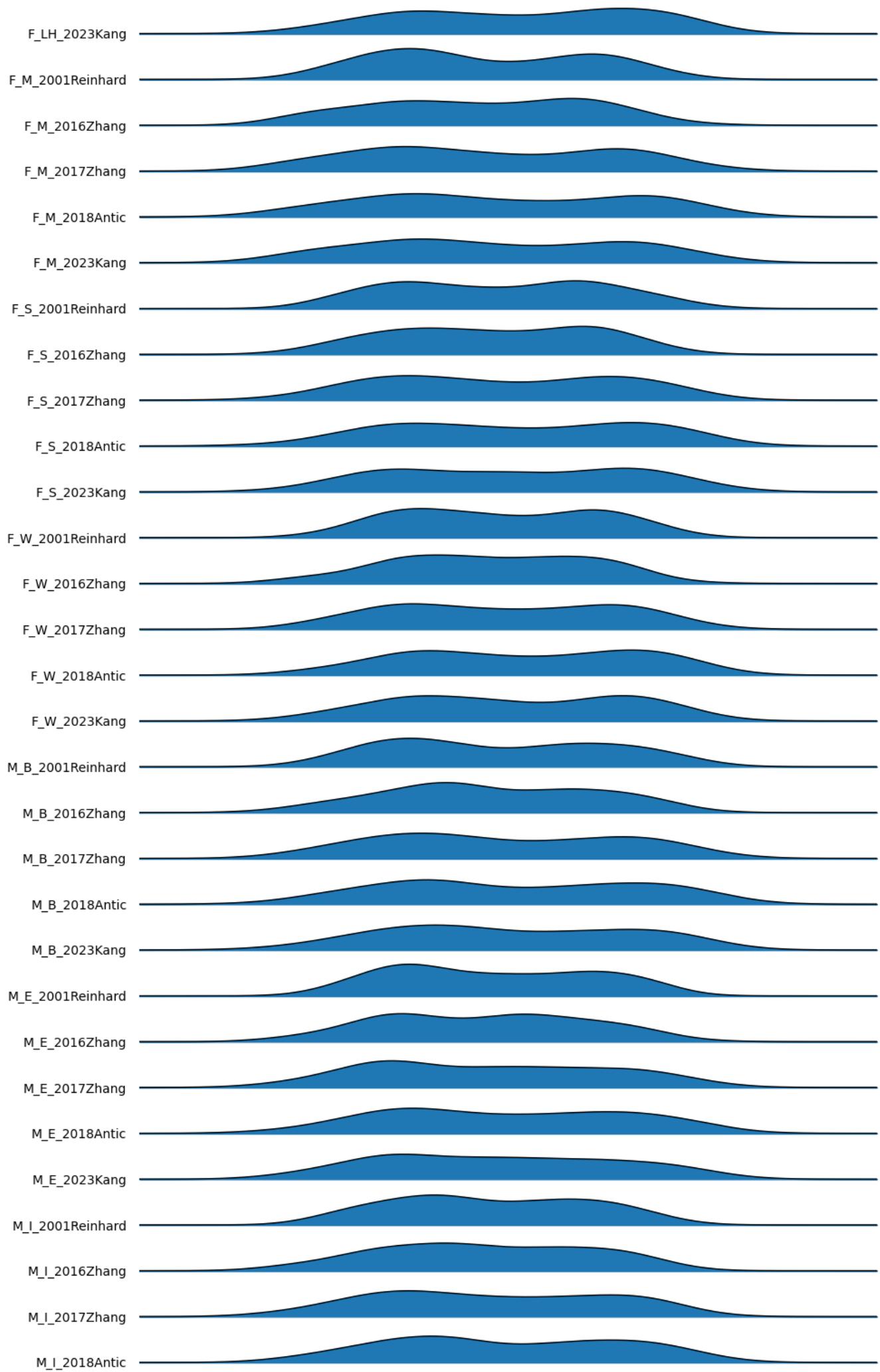
For each metric, we created two-dimensional facets based on all 6 pairs among age, gender, race, and model. Here we look at an example result for full-reference TOPIQ. We can see that for this metric, scores vary widely by model, whereas only small effects can be seen for gender.

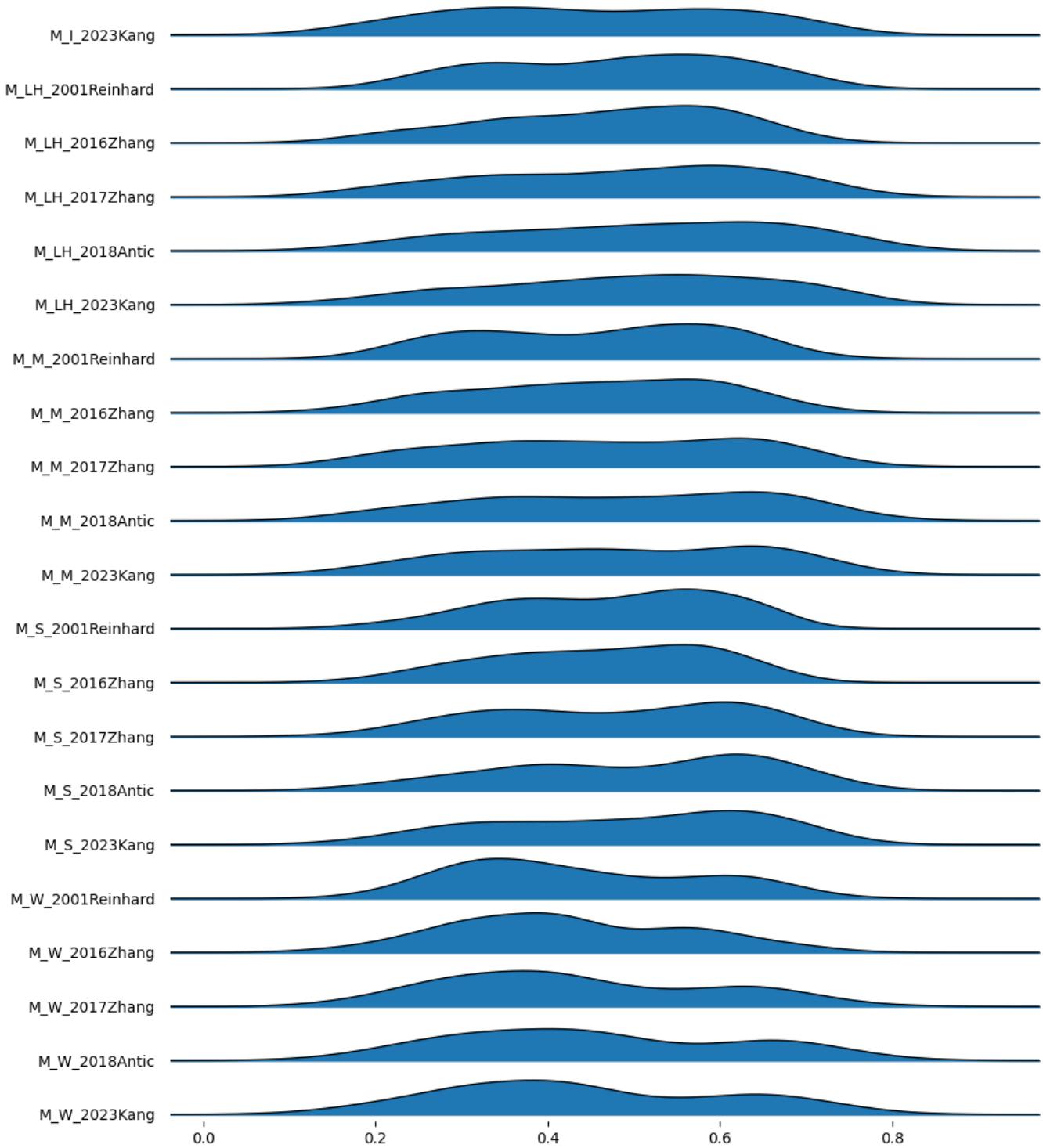


Joyplots

To get a big picture understanding of score range and behavior across groups for each metric, we created joyplots for all 16 subsets of age-gender-race-model. Here, we have the gender-race-model joyplot for ARNIQA.







Summary Statistics

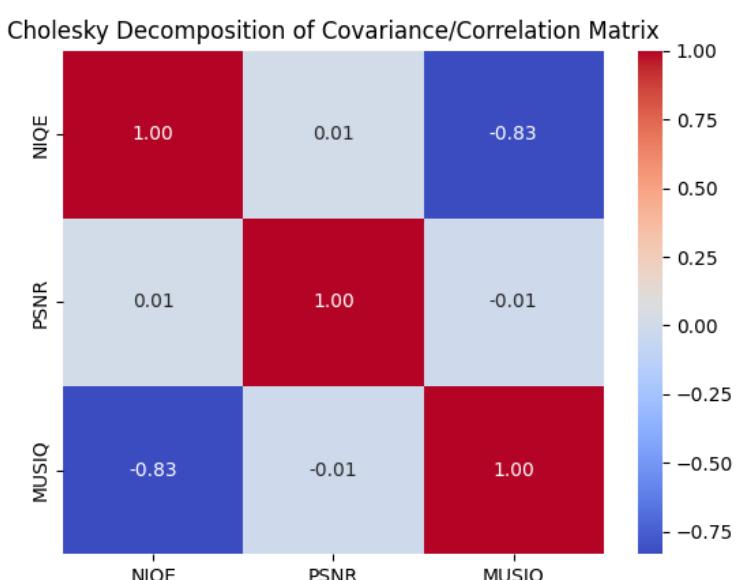
Our last batch of exploratory data analysis for each metric was creating summary statistics. We computed all 1440 age-gender-race-model combinations inclusive of an **All** keyword to cover varying aggregations. Below are the top 20 rows of summary statistics for PSNR.

Age	Gender	Race	Model	Mean	Median	Standard Deviation	IQR	Lower Better
All	All	All	All	23.746290785512883	23.62385654449463	4.551968465979468	4.869461536407467	False
0-2	All	All	All	23.25450802035146	23.096850395202637	4.574577868895466	4.806198596954346	False
10-19	All	All	All	23.41152549409247	23.204188346862793	4.093194870515825	5.070611000061035	False
20-29	All	All	All	24.29193657775978	24.058866500854492	4.462347841180699	4.631749629974365	False
3-9	All	All	All	22.80049496625925	22.655241012573242	4.212472107822797	4.988142490386966	False

Age	Gender	Race	Model	Mean	Median	Standard Deviation	IQR	Lower Better
30-39	All	All	All	24.109582820496	24.011911392211914	4.54354956306265	5.233553886413574	False
40-49	All	All	All	23.95283812981147	24.06586456298828	4.044056115067646	5.028602123260498	False
50-59	All	All	All	23.59485093463551	23.695880889892578	4.344434640209412	4.74501466751099	False
60-69	All	All	All	24.039917325973512	23.895816802978516	4.788069408201891	4.582380294799805	False
more than 70	All	All	All	24.26096280023649	23.863627433776855	5.509883090844478	4.566039085388184	False
All	Female	All	All	23.602220069588004	23.4708890914917	4.388108771548343	4.7810282707214355	False
All	Male	All	All	23.890361501437763	23.784811973571777	4.706039406627894	4.937168121337891	False
All	All	Black	All	23.5398264986096	23.437650680541992	4.60592190395045	4.775972366333011	False
All	All	East Asian	All	23.597166728491736	23.55604362487793	4.239379111993309	4.737373352050781	False
All	All	Indian	All	23.692256008494983	23.605233192443848	4.544037389637518	5.095743656158447	False
All	All	Latino_Hispanic	All	23.912411434481843	23.870217323303223	4.425471819034588	4.806936740875244	False
All	All	Middle Eastern	All	24.27284752046219	23.935327529907227	4.973672409091583	4.832328796386719	False
All	All	Southeast Asian	All	23.386926381274908	23.245975494384766	4.832221078581255	5.064819812774658	False
All	All	White	All	23.82260092677492	23.65176773071289	4.134025545706683	4.709608078002926	False
All	All	All	2001 Reinhard	25.121037349384412	24.09907341003418	6.857395120869607	4.674080848693848	False

Multivariate Mixed-Effects Model

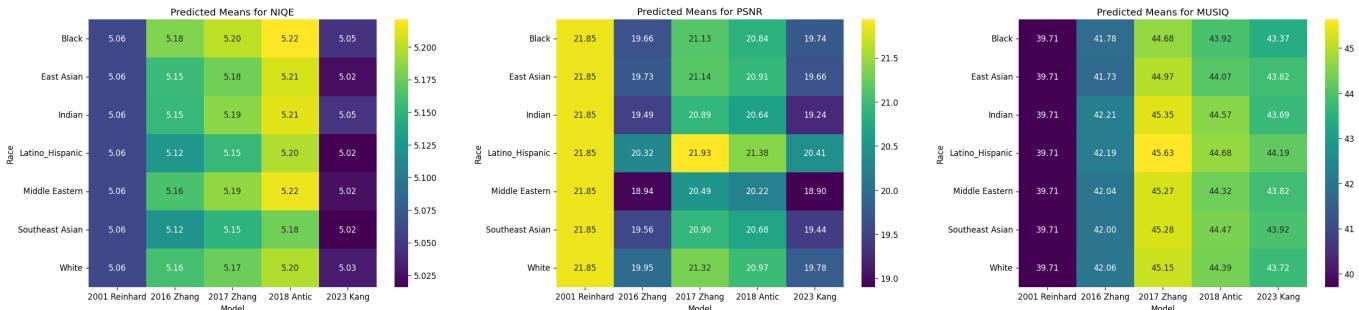
Fitting our reduced-scale multivariate mixed-effects model with 1000 draws and 2 chains took 3 hours, after which we stored our trace in `multivariate_mixed_effects_model_trace.nc`. For our particular run, our randomly selected subset of metrics consisted of NIQE, PSNR, and MUSIQ. PyMC reported that the effective sample size per chain was smaller than 100 for some parameters, which was expected given our limited image dataset. From our resulting trace, we focused on our coefficients and covariances by creating 2 files: `multivariate_mixed_effects_model_cov.csv` and `multivariate_mixed_effects_model_betas.csv`. In our covariances file, we saw that out of the 3 pairs among the 3 metrics, 1 featured a large correlation. Specifically, we saw that NIQE and MUSIQ scores had a correlation of -0.83\$. This supports our model design as utilizing a multivariate approach allowed us to capture important cross-metric relationships that would have been missed by modeling each metric independently. We can also see this visually through a heatmap.



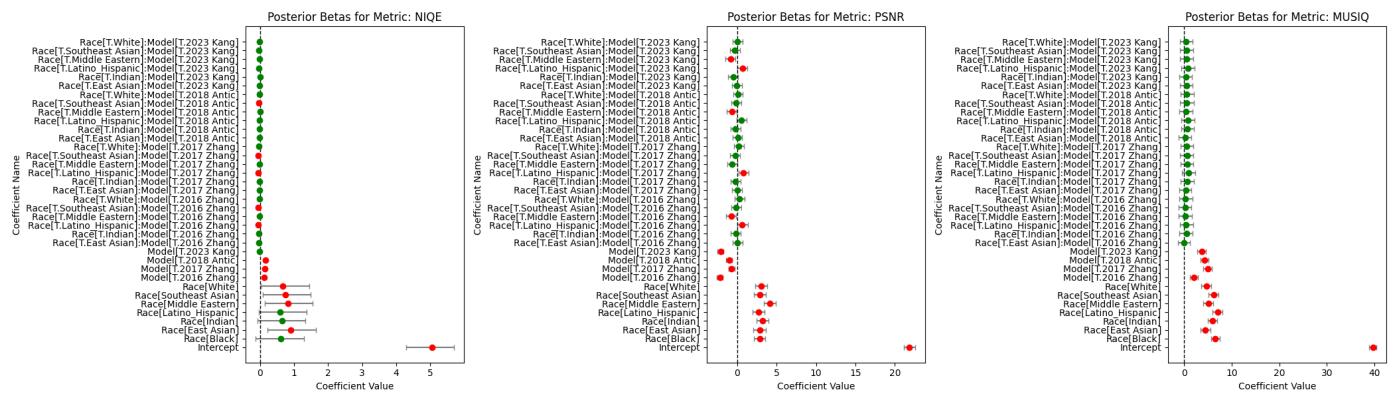
Next, we look at our coefficients. `multivariate_mixed_effects_model_betas.csv` contains simple posterior means for each of them, provided below. We can see that the race fixed effects are varied, aligning with extant research on disparities in recolorization across demographic lines. Interestingly, we can see that the race fixed effects are larger than the model fixed effects by factor of between 2 to 5. One possible interpretation is that race appears to be a stronger driver of the quality metrics than the choice of model. Put differently, the variation associated with race tends to be larger than that associated with the specific recoloring models, which may indicate that demographic factors exert a more pronounced effect on these image-quality scores than do the technical differences among the models themselves. Lastly, race-model interaction effects are smaller than the model fixed effects by around a factor of 5 to 10. This suggests that the differences in reconstruction disparities by model are relatively small and may be overshadowed by the effect of race primarily and model secondarily.

	NIQE	PSNR	MUSIQ
Intercept	5.060283141282467	21.850344635675935	39.70699187448829
Race[Black]	0.6000884931398262	2.8729247347165816	6.508977824654503
Race[East Asian]	0.89516791264898	2.9067844201644286	4.440394467063581
Race[Indian]	0.6441194785108671	3.23664116028621	5.905590066157679
Race[Latino_Hispanic]	0.5923991827540878	2.708096299423645	7.002173510585236
Race[Middle Eastern]	0.8192248728228303	4.153553727626101	5.059262468163551
Race[Southeast Asian]	0.7520144510054835	2.8719166527651994	6.163102680079169
Race[White]	0.6737104746614853	3.02270396364587	4.673038460568174
Model[T.2016 Zhang]	0.12096468597355128	-2.185842000400737	2.0741168519737836
Model[T.2017 Zhang]	0.1406425696650069	-0.7249624835733572	4.968757685170762
Model[T.2018 Antic]	0.16071383874376968	-1.0130095083820558	4.215375696605231
Model[T.2023 Kang]	-0.014479470939951292	-2.1110958541640974	3.667635560046014
Race[T.East Asian]:Model[T.2016 Zhang]	-0.026632328761105207	0.06730397673207372	-0.05303037459719825
Race[T.Indian]:Model[T.2016 Zhang]	-0.027666271388890395	-0.1773068304189067	0.42801228562198373
Race[T.Latino_Hispanic]:Model[T.2016 Zhang]	-0.05636619494821846	0.651769642679341	0.41042514102181643
Race[T.Middle Eastern]:Model[T.2016 Zhang]	-0.019168640720763536	-0.7286805098315275	0.25482313546395224
Race[T.Southeast Asian]:Model[T.2016 Zhang]	-0.06022229162488717	-0.1021376179542452	0.21730789400097802
Race[T.White]:Model[T.2016 Zhang]	-0.021289234730998717	0.28348184867276843	0.27677534577534124
Race[T.East Asian]:Model[T.2017 Zhang]	-0.024293752199225836	0.014075138402236178	0.29072814853946816
Race[T.Indian]:Model[T.2017 Zhang]	-0.0156207261153227	-0.23091603367074978	0.6715332575198492
Race[T.Latino_Hispanic]:Model[T.2017 Zhang]	-0.04794233548699262	0.8080596602549058	0.9555123810862369
Race[T.Middle Eastern]:Model[T.2017 Zhang]	-0.013689882994059129	-0.6318558898572451	0.5957012497134112
Race[T.Southeast Asian]:Model[T.2017 Zhang]	-0.05274394533224977	-0.22398758621325937	0.601222626504729
Race[T.White]:Model[T.2017 Zhang]	-0.02628761806426145	0.19330820191179926	0.4738587995877262
Race[T.East Asian]:Model[T.2018 Antic]	-0.013329194269764309	0.0775599147063064	0.14367161091806552
Race[T.Indian]:Model[T.2018 Antic]	-0.008908166407270516	-0.19874536570138449	0.6502335813948643
Race[T.Latino_Hispanic]:Model[T.2018 Antic]	-0.02415333028980977	0.547549830056663	0.7608298847537859
Race[T.Middle Eastern]:Model[T.2018 Antic]	-0.004811280857178096	-0.6190992015512617	0.3982356959591106
Race[T.Southeast Asian]:Model[T.2018 Antic]	-0.04439672593345831	-0.1563903233116077	0.5476756808469783
Race[T.White]:Model[T.2018 Antic]	-0.023450212052056052	0.12905259044665227	0.4707036436946758
Race[T.East Asian]:Model[T.2023 Kang]	-0.022795537513443005	-0.07597139427979421	0.45028419574094836
Race[T.Indian]:Model[T.2023 Kang]	0.0006812101399671387	-0.49907602205948925	0.3129529167253949
Race[T.Latino_Hispanic]:Model[T.2023 Kang]	-0.029071424144081773	0.6700879515593461	0.8155858347253488
Race[T.Middle Eastern]:Model[T.2023 Kang]	-0.02115481870964301	-0.8380218904563208	0.44282795290506344
Race[T.Southeast Asian]:Model[T.2023 Kang]	-0.029819395203354318	-0.30058781974814647	0.547453352977678
Race[T.White]:Model[T.2023 Kang]	-0.014168884235001126	0.04211331421446757	0.3444059407203242

Using these data, we can then reconstruct and visualize metric estimates by race and model.



Lastly, we can interpret the significance of each term at the standard significance level by leveraging caterpillar plots and the concept of highest density intervals. We can see that for PSNR and MUSIQ, all model factors and all race factors are significant, providing evidence of disparities in reconstruction scores by demographics. For NIQE, we have 1 insignificant model factor and 3 insignificant race factors, seemingly due to the large uncertainty of these estimates. Moving on to race-model interactions, we see that NIQE and PSNR respectively have 5 and 6 significant terms, suggesting that there may be differences in reconstruction disparities by model. However, it should be noted that we do not see any significant terms for MUSIQ.



Overall, our results seem to reaffirm extant research on disparities in colorization by demographics and indicate that these disparities to some extent may differ by model, though further work is needed to verify these results.

Limitations

A major simplifying assumption in our research project was that the image quality assessment metrics themselves are unbiased and do not systematically vary by demographic groups. However, this may not actually be the case, especially given that no-reference metrics in particular learn from real-world image datasets, which are prone to bias. Another one of the limitations of our analysis was our limited sample size per demographic subgroup, as we only had access to 22 images per group. This restricted the generalizability of our results, but future work can look at gaining access to larger annotated datasets. Additionally, the size of our suite of implemented models constrained our ability to understand differences in reconstruction disparities over time, though more models can be integrated going forward. We also faced challenges incorporating age, gender, and their additional associated interaction terms into our model due to computing constraints. However, future work can expand upon our base design. Another issue was that we lost a more nuanced understanding of how disparities manifest across multiple quality dimensions in leveraging a random 3-sized subset of our 28 metrics, but this can be rectified with further computation. Lastly, our multivariate mixed-effects model itself rests upon several assumptions. These include the linearity of fixed effects, normality of random effects, and independence and homoscedasticity of residuals. While many of these are reasonable assumptions for our particular domain, future work can verify if these assumptions hold.

Conclusion

Analyzing how colorful bias has changed over time brings us closer to understanding how we might proactively create systems and algorithms to combat it. From diversity in image datasets, knowledge of historical and cultural context, and conceptions of palatable color schemes, deconstructing exact sources of bias remains an open challenge as detailed in [The Limits of AI Image Colorization: A Companion](#) (Goree, 2021). While new formulations for bias metrics such as those introduced in [Bias in Automated Image Colorization: Metrics and Error Types](#) further complicate this endeavor [77], the increased focus on these normative questions in the space of image colorization in recent years brings hope for fairer and more inclusive technological progress.

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