

# Gender Slopes: Counterfactual Fairness for Computer Vision Models by Attribute Manipulation

Jungseock Joo\*  
UCLA

Kimmo Kärkkäinen  
UCLA

## Abstract

Automated computer vision systems have been applied in many domains including security, law enforcement, and personal devices, but recent reports suggest that these systems may produce biased results, discriminating against people in certain demographic groups. Diagnosing and understanding the underlying true causes of model biases, however, are challenging tasks because modern computer vision systems rely on complex black-box models whose behaviors are hard to decode. We propose to use an encoder-decoder network developed for image attribute manipulation to synthesize facial images varying in the dimensions of gender and race while keeping other signals intact. We use these synthesized images to measure counterfactual fairness of commercial computer vision classifiers by examining the degree to which these classifiers are affected by gender and racial cues controlled in the images, e.g., feminine faces may elicit higher scores for the concept of nurse and lower scores for STEM-related concepts. We also report the skewed gender representations in an online search service on profession-related keywords, which may explain the origin of the biases encoded in the models.

## Introduction

Artificial Intelligence has made remarkable progress in the past decade. Numerous AI-based products have already become prevalent in the market, ranging from robotic surgical assistants to self-driving vehicles. The accuracy of AI systems has surpassed human capability in challenging tasks, such as face recognition (Taigman et al., 2014), lung cancer screening (Ardila et al., 2019) and pigmented skin lesion diagnosis (Tschandl et al., 2019). These practical applications of AI systems have prompted attention and support from industry, academia, and government.

While AI technologies have contributed to increased work productivity and efficiency, a number of reports have also been made on the algorithmic biases and discrimination caused by data-driven decision making in AI systems. For example, COMPAS, an automated risk assessment tool used in criminal justice (Brennan, Dieterich, and Ehret, 2009), was reported to contain bias against Black defendants by assigning higher risk scores to Black defendants than White defendants (Angwin et al., 2019). Another recent study also reports the racial and gender bias in computer vision APIs

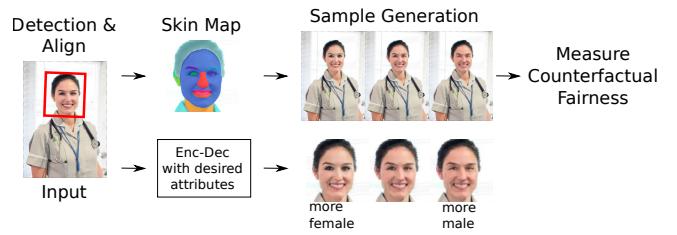


Figure 1: Overview of our method for counterfactual image synthesis.

for facial image analysis, which were shown less accurate on certain race or gender groups (Buolamwini and Gebru, 2018).

How can biased machine learning and computer vision models impact our society? We consider a following example. Let's suppose an online search engine, such as Google, tries to make a list of websites of medical clinics and sort them by relevance. This list may be given to users as a search result or advertising content. The search algorithm will use content in websites to determine and rank their relevance, and any visual content, such as portraits of doctors, may be used as a feature in the pipeline. If the system relies on a biased computer vision model in this pipeline, the overall search results may also inherit the same biases and eventually affect users' decision makings. Scholars have discussed and found present biases in online media such as skewed search results (Goldman, 2008) or gender difference in STEM career ads (Lambrecht and Tucker, 2019), yet little has been known about mechanisms or origins of such biases.

While previous reports have shown that popular computer vision and machine learning models contain biases and exhibit disparate accuracies on different subpopulations, it is still difficult to identify true causes of these biases. This is because one cannot know to which variable or factor the model responds. If we wish to verify if a model indeed discriminates against a sensitive variable, e.g., gender, we need to isolate the factor of gender and intervene its value for **counterfactual** analysis (Hardt et al., 2016).

The objective of our paper is to adopt an encoder-decoder architecture for facial attribute manipulation (Lample et al., 2017) and generate counterfactual images which vary

\*jjoo@comm.ucla.edu

along the dimensions of sensitive attributes: gender and race. These synthesized examples are then used to measure counterfactual fairness of black-box image classifiers offered by commercial providers. Figure 1 shows the overall process of our approach. Given an input image, we detect a face and generate a series of novel images by manipulating the target sensitive attributes while maintaining other attributes. We summarize our main contributions as follows.

1. We propose to use an encoder-decoder network (Lample et al., 2017) to generate novel face images, which allows counterfactual interventions. Unlike previous methods (Denton et al., 2019), our method explicitly isolates the factors for sensitive attributes, which is critical in identifying true causes to model biases.
2. We construct a novel image dataset which consists of 64,500 original images collected from web search and more than 300,000 synthesized images manipulated from the original images. These images describe people in diverse occupations and can be used for studies on bias measurement or mitigation. Both the code and data will be made publicly available.
3. Using new methods and data, we measure counterfactual fairness of commercial computer vision classifiers and report whether and how sensitive these classifiers are affected along with attributes being manipulated by our model.

## Related Work

**ML and AI Fairness** Fairness in machine learning has recently received much attention as a new criterion for model evaluation (Zemel et al., 2013; Hardt et al., 2016; Zafar et al., 2017; Kilbertus et al., 2017; Kusner et al., 2017). While the quality of a machine learning model has traditionally been assessed by its overall performance such as average classification accuracy measured from the entire dataset, the new fairness measures focus on the consistency of model behavior across distinct data segments or the detection of spurious correlations between target variables (e.g., loan approval) and protected attributes (e.g., race or gender).

The existing literature identifies a number of definitions and measures for ML/AI fairness (Corbett-Davies and Goel, 2018), including fairness through unawareness (Dwork et al., 2012), disparate treatment and disparate impact (Zafar et al., 2017), accuracy disparity (Buolamwini and Gebru, 2018), and equality in opportunity (Hardt et al., 2016). These are necessary because different definitions of fairness should be used in different tasks and contexts.

A common difficulty in measuring fairness is that it is challenging to identify or differentiate true causes of the discriminating model behaviors due to the input data that is built upon combination of many factors. Consequently, it is difficult to conclude that the variations in model outputs are solely caused by the sensitive or protected attributes. To overcome the limitation, Kusner et al. (Kusner et al., 2017) proposed the notion of counterfactual fairness based on causal inference. Here, a model, or predictor, is counterfactually fair as long as it produces an equal output to any

input data whose values for the sensitive attribute are modified by an intervention but otherwise identical. Similar to (Kusner et al., 2017), our framework is based on counterfactual fairness to measure whether the prediction of the model differs by the *intervened* gender of the input image, while separating out the influences from all the other factors in the background.

**Fairness and Bias in Computer Vision** Fairness in computer vision is becoming more critical as many systems are being adapted in real world applications. For example, face recognition systems such as Amazon’s Rekognition are being used by law enforcement to identify criminal suspects (Harwell, 2019). If the system produces biased results (e.g., higher false alarm on Black suspects), then it may lead to a disproportionate arrest rate on certain demographic groups. In order to address this issue, scholars have attempted to identify biased representations of gender and race in public image dataset and computer vision models (Hendricks et al., 2018; Manjunatha, Saini, and Davis, 2019; Kärkkäinen and Joo, 2019; McDuff et al., 2019). Buolamwini and Gebru (Buolamwini and Gebru, 2018) have shown that commercial computer vision gender classification APIs are biased and thus perform least accurately on dark-skinned female photographs. (Kyriakou et al., 2019) has also reported that image classification APIs may produce different results on faces in different gender and race. These studies, however, used the existing images without interventions, and thus it is difficult to identify whether the classifiers responded to the sensitive attributes or to the other visual cues. (Kyriakou et al., 2019) used the headshots of people with clean white background, but this hinders the classifiers from producing many comparable tags.

Our paper is most closely related to Denton et al. (Denton et al., 2019), who use a generative adversarial network (GAN) (Goodfellow et al., 2014) to generate face images to measure counterfactual fairness. Their framework incorporates a GAN trained from a face image dataset called CelebA (Liu et al., 2015), and generates a series of synthesized samples by modifying the latent code in the embedding space to the direction that would increase the strength in a given attribute (e.g., smile). Our paper differs from this work for the following reasons. First, we use a different method to examine the essential concept of counterfactual fairness by generating samples that separate the signals of the sensitive attributes out from the rest of the images. Second, our research incorporates the generated data to measure the bias of black-box image classification APIs whereas (Denton et al., 2019) measures the bias of a dataset open to public (Liu et al., 2015). Using our distinct method and data, we aim to identify the internal biases of models trained from unknown data.

## Counterfactual Data Synthesis

### Problem Formulation

The objective of our paper is to measure counterfactual fairness of a predictor  $Y$ , a function of an image  $x$ . This predictor is an image classifier that automatically labels the content of input images. Without the loss of generality, we consider

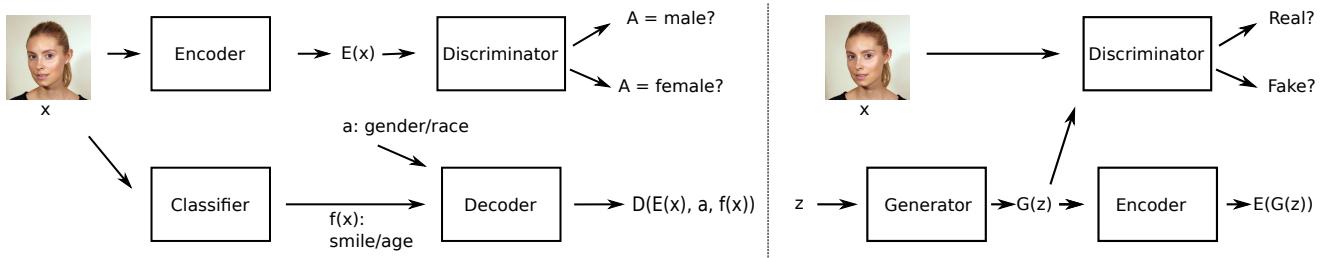


Figure 2: Illustrations of (left) our encoder-decoder architecture based on FaderNetwork (Lample et al., 2017) and (right) a GAN used by Denton et al. (Denton et al., 2019). Our model explicitly separates the sensitive attributes from the remaining representation encoded in  $E(x)$ . In both models, the discriminator is optimized by adversarial training.



Figure 3: Our model controls for non-central attributes such as smiling and age. These attributes (e.g., mouth open) are fixed while the main attribute (race) is manipulated.

a binary classifier,  $Y(x) = \{True, False\}$ . This function classifies, for example, whether the image displays a doctor or not. We also define a sensitive attribute,  $A$ , gender and race. Typically,  $A$  is a binary variable in the training data, but it can take a continuous value in our experiment since we can manipulate the value without restriction. Following (Hardt et al., 2016), this predictor satisfies counterfactual fairness if  $P(Y_{A \leftarrow a}(x) = y|x) = P(Y_{A \leftarrow a'}(x) = y|x)$  for all  $y$  and any  $a$  and  $a'$ , where  $A \leftarrow a$  indicates an intervention on the sensitive attribute,  $A$ . We now explain how this is achieved by an encoder-detector network.

The goal of this intervention is to manipulate an input image such that it changes the cue related to the sensitive attribute while retaining all the other signals. We consider two sensitive attributes: gender and race. We manipulate facial appearance because face is the strongest cue for gender and race identification (Moghaddam and Yang, 2002).

## Counterfactual Data Synthesis

Before we elaborate our proposed method for manipulating sensitive attributes, we briefly explain why such a method is necessary to show if a model achieves counterfactual fairness. For an in-depth introduction to the framework of counterfactual fairness, we refer the reader to Kusner et al. (Kusner et al., 2017).

Many studies have reported skewed classification accuracy of existing computer vision models and APIs between

gender and racial groups (Buolamwini and Gebru, 2018; Kyriakou et al., 2019; Kärkkäinen and Joo, 2019; Zhao et al., 2017). However, these findings are based on a comparative analysis, which directly compares the classifier outputs between male and female images (or White and non-White) in a given dataset. The limitation of the method is that it is difficult to identify true sources of biased model outputs due to hidden confounding factors. Even though one can empirically show differences between gender groups, such differences may have been caused by non-gender cues such as hair style or image backgrounds (see (Muthukumar et al., 2018), for example). Since there exists an infinite number of possible confounding factors, it will be very difficult to control for all of them.

Consequently, recent works in bias measurement or mitigation have adopted generative models which can synthesize or manipulate text or image data (Denton et al., 2019; Zmigrod et al., 2019). These methods generate hypothetical data in which only sensitive attributes are switched. These data can be used to measure counterfactual fairness but also augment samples in existing biased datasets.

## Face Attribute Synthesis

From the existing methods available for face attribute manipulation (Yan et al., 2016; Bao et al., 2017; He et al., 2019), we chose FaderNetwork (Lample et al., 2017) as our base model. FaderNetwork is a computationally efficient model that produces plausible results, but we made a few changes to make it more suitable for our study.

Figure 2 illustrates the flows of our model and (Denton et al., 2019). The model used in (Denton et al., 2019) is based on a GAN that is trained without using any attribute labels. As in standard GANs, this model learns the latent code space from the training set. This space encodes various information such as gender, age, race, and any other cues necessary for generating a facial image. These factors are all entangled in the space, and thus it is hard to control only the sensitive attribute, which is required for the purpose of counterfactual fairness measurement. In contrast, FaderNetwork directly observes and exploits the sensitive attributes in training and makes its latent space invariant to them.

Specifically, FaderNetwork is based on an encoder-

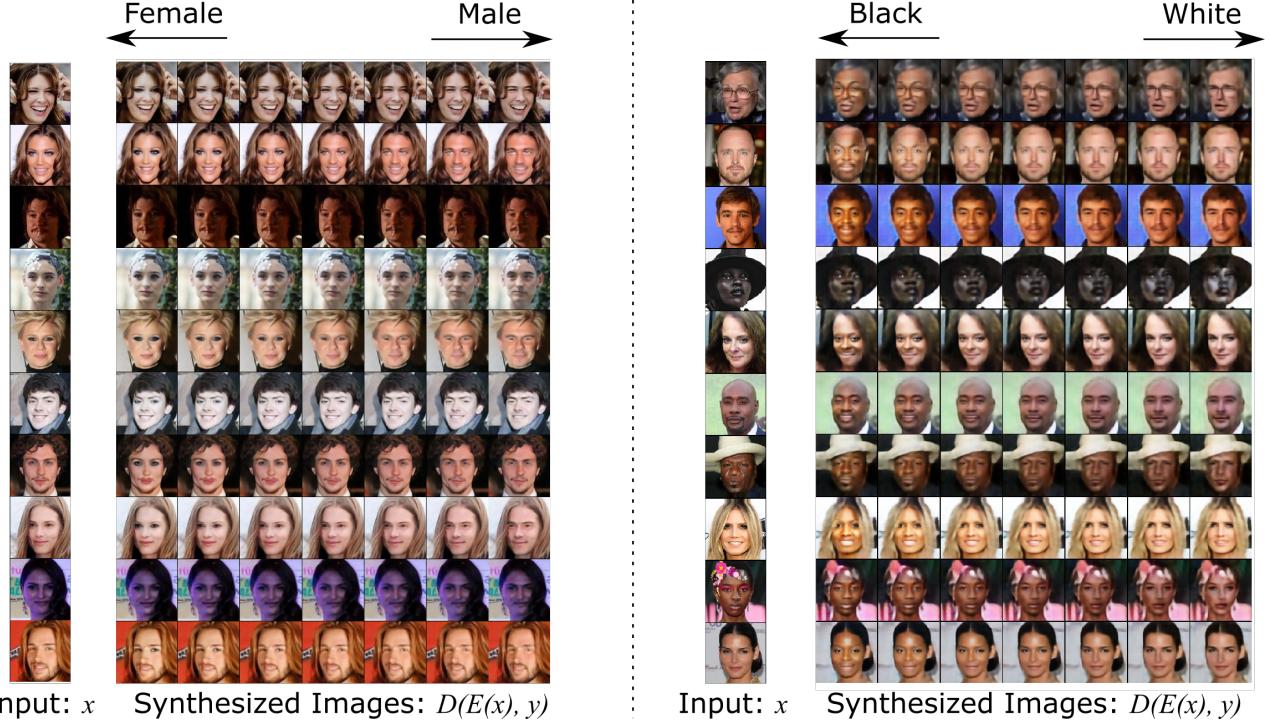


Figure 4: Examples generated by our models, manipulated in (left) gender and (right) race.

decoder network with two special properties. First, it separates the sensitive attribute,  $a$ , from its encoder output,  $E(x)$ , and both are fed into the decoder, such that it can reconstruct the original image, i.e.,  $D(E(x), a) \approx x$ . Second, it makes  $E(x)$  invariant to  $a$  by using adversarial training such that the discriminator cannot predict the correct value for  $a$  given  $E(x)$ . At test time, an arbitrary value for  $a$  can be given to obtain an image with a modified attribute value.

Since we want to minimize the change by the model to dimensions other than the sensitive attributes, we added two additional steps as follows. First, we segment the facial skin region from an input face by (Yu et al., 2018)<sup>1</sup> and only retain changes within the region. This prevents the model from affecting background or hair regions. Second, we control for the effects of other attributes (e.g., smiling or young) which may be correlated with the main sensitive attribute, such that their values remain intact while being manipulated. This was achieved by first modeling these attributes as the main sensitive attributes along with  $y$  in training and fixing their values at testing time. This step may look unnecessary because the model is expected to separate all gender (or any other sensitive attributes) related information. However, it is important to note that the dataset used to train our model may also contain biases and it is hard to guarantee that its sensitive attributes are not correlated with other attributes. By enforcing the model to produce fixed outputs, we can explicitly control for those variables (similar ideas have been used in recent work on attribute manipulation (He et al., 2019)). Figure 3 shows the comparison between our model and the

original FaderNetwork. This approach allows our model to minimize the changes in dimensions other than the main attribute being manipulated. Figure 4 shows randomly chosen results by our method.

## Experiments

### Computer Vision APIs

We measured counterfactual fairness of commercial computer vision APIs which provide label classification for a large number of visual concepts, including Google Vision API, Amazon Rekognition, IBM Watson Visual Recognition, and Clarifai. These APIs are widely used in commercial products as well as academic research (Xi et al., 2019). While public computer vision datasets usually focus on general concepts (e.g., 60 common object categories in MS COCO (Lin et al., 2014)), these services generate very specific and detailed labels on thousands of distinct concepts. While undoubtedly useful, these APIs have not been fully verified for their fairness. They may be more likely to generate more “positive” labels for people in certain demographic groups. These labels may include highly-paid and competitive occupations such as “doctor” or “engineer” or personal traits such as “leadership” or “attractive”. We measure the sensitivity of these APIs using counterfactual samples generated by our models.

### Occupational Images

We constructed the baseline data that can be used to synthesize samples. We are especially interested in the effects of gender and race changes on the profession related labels

<sup>1</sup><https://github.com/zllrunning/face-parsing.PyTorch>

provided by the APIs, and thus collected a new dataset of images related to various professions. We first obtained a list of 129 job titles from the Bureau of Labor Statistics (BLS) website and used Google Image search to download images. Many keywords resulted in biased search results in terms of the gender and race ratio. To obtain more diverse images, we additionally combined six different keywords (male, female, African American, Asian, Caucasian, and Hispanic). This results in around 250 images per keyword. We disregarded images without any face.

We also needed datasets for training our model. For the gender manipulation model, we used CelebA (Liu et al., 2015), which is a very popular face attribute dataset with 40 labels annotated for each face. This dataset mostly contains the faces of White people, and thus is not suitable for the race manipulation model. There is no publicly available dataset with a sufficiently large number of African Americans. Instead, we obtained the list of the names of celebrities for each gender and each ethnicity from an online website, FamousFix. Then we used Google Image search to download up to 30 images for each celebrity. We estimated the true gender and race of each face by a model trained from a public dataset (Kärkkäinen and Joo, 2019) and manually verified examples with lower confidences. Finally, this dataset was combined with CelebA to train the race manipulation model.

After training, two models (gender and race) were applied to the profession dataset to generate a series of manipulated images for each input image. If there are multiple faces detected in an image, we only manipulated the face closest to the center of it. These faces are pasted into the original image, only on the facial skin region, and passed to each of the 4 APIs we tested. All the APIs provide both the presence of each label (binary) and the continuous classification confidence if the concept is present in the image. Figure 4 shows example images manipulated in gender and race.

## Results

The sensitivity of a classifier with respect to the changes in gender or race cues of images is measured as a slope estimated from the assigned attribute value,  $a$ , and the model output,  $Y(x(a))$ , where  $x(a)$  is a synthesized image with its attribute manipulated to the value  $a$ . The range of  $a$  was set to  $(-2, 2)$ . The center, i.e., gender-neutral face, is 0.  $(-1, 1)$  is the range observed in training, and  $(-2, 2)$  will extrapolate images beyond the training set. In practice, this still results in natural and plausible samples. From this range, we sampled 7 evenly spaced images for gender manipulation and 5 images for race manipulation.<sup>2</sup> Let us denote  $x^i$ , the  $i$ -th input image, and  $\{x_1^i, \dots, x_K^i\}$ , the set of  $K$  synthesized images ( $K = 7$ ). For each label in  $Y$ , we obtain 7 scores. From the entire image set  $\{x^i\}$ , we obtain a normal-

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<sup>2</sup>We reduced the number from 7 to 5 as this was more cost effective and sufficient to discover the correlation between the attributes and output labels.

ized classifier output vector:

$$y_k = \frac{1}{n} \sum_i \mathbb{1}\{Y(x_k^i) = \text{True}\}, k \in \{1, \dots, K\},$$

$$z_k = y_k / y_c, c = (K + 1)/2.$$

That is, we normalize the vector such that  $z_c$  is always 1 to allow comparisons across concepts. The slope  $b$  is obtained by linear regression with ordinary least squares. The magnitude of  $b$  determines the sensitivity of the classifier against  $a$ , and its sign indicates the direction.

Table 1 and 2 show the list of labels returned by each API, more frequently activated with images manipulated to be closer to women and to men, respectively. Not surprisingly, we found the models behave in a closely related way to the actual gender gap in many occupations such as nurses or scientists (see Figure 5, too). One can imagine this bias was induced at least in part due to the bias in the online media and web, from which the commercial models have been trained. Table 3 and 4 show skewed gender and race representations in our main dataset of peoples' occupations. Indeed, many occupations such as nurse or engineer exhibit very sharp gender contrast, and this may explain the behaviors of the image classifiers. Figure 6 shows example images and their label prediction scores.<sup>3</sup>

Similarly, Table 5 and 6 show the labels which are most sensitive to the race manipulation. The tables show all the dimensions which are significantly correlated with the model output ( $p < 0.001$ ), except plain concepts such as "Face" or "Red color". We found the APIs are in general less sensitive to race change than gender change.

## Conclusion

AI fairness is an increasingly important criterion to evaluate models and systems. In real world applications, especially for private models whose training processes or data are unknown, it is difficult to identify their biased behaviors or to understand the underlying causes. We introduced a novel method based on facial attribute manipulation by an encoder-decoder network to synthesize counterfactual samples, which can help isolate the effects of the main sensitive variables on the model outcomes. Using this methodology, we were able to identify hidden biases of commercial computer vision APIs on gender and race. These biases, likely caused by the skewed representation in online media, should be adequately addressed in order to make these services more reliable and trustworthy.

## Acknowledgement

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<sup>3</sup>The APIs output a binary decision and a prediction confidence for each label. Our analysis is based on binary values (true or false), and we found that using confidence scores makes little difference in the final results.

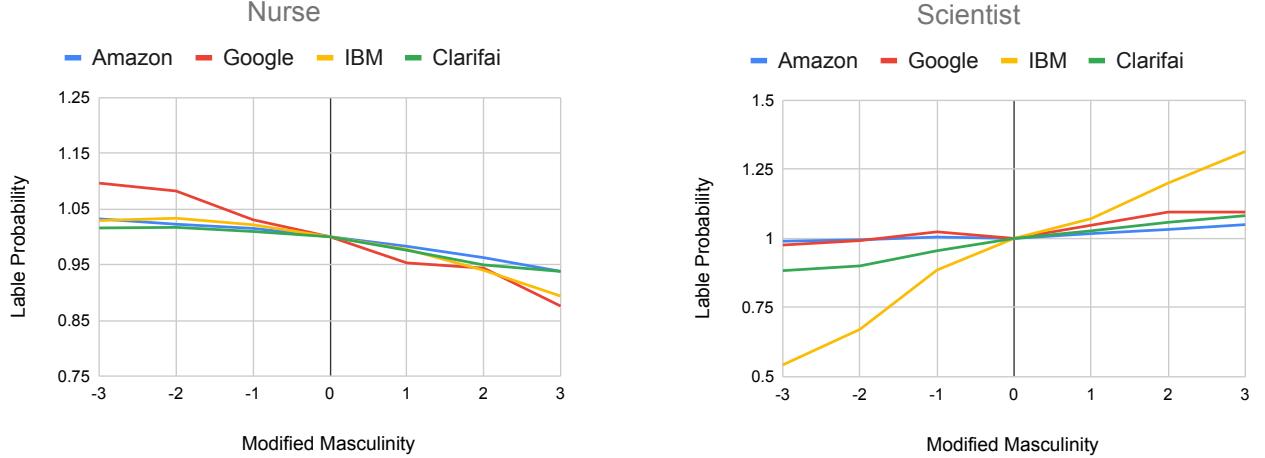


Figure 5: The sensitivity of image classification APIs for Nurse and Scientist to the modified facial gender cues.

Table 1: The Sensitivity of Label Classification APIs against Gender Manipulation (Female). (Only showing labels with p-value < 0.001 and | slope | > 0.03).

API	Label	Slope
Amazon	Nurse	-0.031
Google	Fashion model	-0.262
Google	Model	-0.261
Google	Secretary	-0.14
Google	Nurse	-0.073
IBM	anchorman	-0.213
IBM	television reporter	-0.155
IBM	college student	-0.151
IBM	legal representative	-0.147
IBM	careerist	-0.128
IBM	host	-0.125
IBM	steward	-0.11
IBM	Secretary of State	-0.107
IBM	gynecologist	-0.099
IBM	celebrity	-0.097
IBM	newsreader	-0.09
IBM	cleaning person	-0.081
IBM	nurse	-0.046
IBM	laborer	-0.044
IBM	workman	-0.041
IBM	entertainer	-0.04
Clarifai	secretary	-0.273
Clarifai	receptionist	-0.268
Clarifai	model	-0.211
Clarifai	shopping	-0.058

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	Female	Original	Male		Female	Original	Male
							
Nurse (G)	.831	.788	.690	Doctor (I)	.627	.723	.762
Surgeon (I)	0	0	.506	Nurse (C)	.962	.929	0
Medical specialist (I)	0	0	.501	Nurse (A)	.670	.666	.618
				Medical specialist (I)	0	.522	.548
				Female	Original	Male	
Nurse (G)	.646	.538	0				
Physician (G)	0	0	.524	Doctor (I)	.744	.783	.828
Nurse (C)	.954	.968	0	Nurse (A)	.887	.882	.813
				Nurse (C)	.958	.941	.902
				Surgeon (C)	.875	.907	.917
				Female	Original	Male	
Research (G)	.675	.721	.769				
Science (G)	0	0	.516	Engineering (G)	.572	.611	.634
Research (C)	0	.851	.873	Science (G)	0	0	.516
Science (C)	0	0	.869	Building (A)	.709	.755	.775
Scientific instrument (I)	.615	.687	.715	Machine (I)	0	.792	.794
				Business (C)	0	0	.861
				Female	Original	Male	
Computer programmer (I)	.500	.580	.613				
Telephone call(I)	.537	.500	0	Engineering (G)	0	.520	.520
				Electronic device (G)	0	.610	.610
				Employment (G)	.665	.623	.582
				Computer programmer (I)	.500	.723	.744
				Teacher (A)	.580	.595	.781

Figure 6: Example images and label prediction scores from APIs (G:Google, A:Amazon, I:IBM, C:Clarifai). “0” means the label was not detected. Blue labels indicate an increasing score with increasing masculinity (red for femininity). Some images were clipped to fit the space. Zoom in to see the details.

Table 2: The Sensitivity of Label Classification APIs against Gender Manipulation (Male). (Only showing labels with p-value < 0.001 and | slope | > 0.03).

API	Label	Slope
Amazon	Attorney	.113
Amazon	Executive	.055
Google	Blue-collar worker	.056
Google	Spokesperson	.040
Google	Engineer	.038
IBM	scientist	.254
IBM	sociologist	.213
IBM	investigator	.174
IBM	sports announcer	.164
IBM	resident commissioner	.159
IBM	repairer	.151
IBM	Representative	.142
IBM	cardiologist	.140
IBM	high commissioner	.134
IBM	security consultant	.131
IBM	speaker	.122
IBM	internist	.119
IBM	Secretary of the Int.	.114
IBM	biographer	.109
IBM	military officer	.107
IBM	radiologist	.082
IBM	detective	.081
IBM	diplomat	.063
IBM	contractor	.061
IBM	player	.061
IBM	medical specialist	.050
IBM	official	.049
IBM	subcontractor	.043
Clarifai	film director	.342
Clarifai	machinist	.192
Clarifai	writer	.153
Clarifai	repairman	.125
Clarifai	surgeon	.087
Clarifai	inspector	.085
Clarifai	waiter	.082
Clarifai	worker	.078
Clarifai	scientist	.070
Clarifai	singer	.056
Clarifai	musician	.056
Clarifai	construction worker	.053
Clarifai	police	.054
Clarifai	athlete	.048
Clarifai	politician	.037

Table 3: Skewed gender representations in Google Image search result

Occupation	Female %	Occupation	Male %
nutritionist	.921	pest control worker	.971
flight attendant	.891	handyman	.964
hair stylist	.884	logging worker	.950
nurse	.860	basketball player	.925
medical assistant	.847	businessperson	.920
dental assistant	.835	chief executive officer	.917
merchandise display	.821	lawn service worker	.909
nursing assistant	.821	electrician	.901
dental hygienist	.815	barber	.901
veterinarian	.784	repair worker	.900
fashion designer	.775	sales engineer	.889
occupational therapy asst.	.772	construction worker	.887
librarian	.770	maintenance worker	.882
office assistant	.759	officer	.882
receptionist	.745	radio operator	.871
travel agent	.734	music director	.868
medical transcriptionist	.732	software developer	.857
preschool teacher	.730	golf player	.855
teacher assistant	.728	CTO	.846
counselor	.728	mechanic	.836

Table 4: Skewed race representations in Google Image search result

Occupation	White %	Occupation	White %
historian	.885	basketball player	.200
building inspector	.875	farmworker	.231
funeral director	.852	ahtlete	.415
construction inspector	.847	software developer	.429
glazier	.846	product promoter	.451
legislator	.840	interpreter	.457
animal trainer	.839	barber	.457
boiler installer	.836	medical assistant	.459
jailer	.823	food scientist	.462
judge	.822	chemical engineer	.488
handyman	.821	database administrator	.489
baker	.818	computer network architect	.500
firefighter	.815	industrial engineer	.513
veterinarian	.811	driver	.514
pilot	.797	bus driver	.532
optician	.795	fashion designer	.539
businessperson	.793	security guard	.539
CFO	.791	mechanic	.548
maintenance manager	.791	nurse	.548
secretary	.785	cashier	.549

Table 5: The Sensitivity of Label Classification APIs against Race Manipulation (Black). (Only showing labels with p-value < 0.001 and | slope | > 0.03).

API	Label	Slope
IBM	woman orator	-0.69
IBM	President of the U.S.	-0.367
IBM	first lady	-0.323
IBM	high commissioner	-0.284
IBM	Representative	-0.225
IBM	scientist	-0.183
IBM	worker	-0.131
IBM	resident commissioner	-0.116
IBM	sociologist	-0.099
IBM	analyst	-0.09
IBM	call center	-0.085
IBM	diplomat	-0.085
Clarifai	democracy	-0.09
Clarifai	musician	-0.063
Clarifai	singer	-0.046
Clarifai	cheerful	-0.044
Clarifai	happiness	-0.034
Clarifai	music	-0.033
Clarifai	confidence	-0.032

Table 6: The Sensitivity of Label Classification APIs against Race Manipulation (White). (Only showing labels with p-value < 0.001 and | slope | > 0.03).

API	Label	Slope
IBM	careerist	0.179
IBM	dermatologist (doctor)	0.127
IBM	legal representative	0.111
IBM	business man	0.093
IBM	entertainer	0.034
Clarifai	repair	0.074
Clarifai	beautiful	0.074
Clarifai	repairman	0.073
Clarifai	writer	0.054
Clarifai	physician	0.053
Clarifai	work	0.051
Clarifai	professional person	0.05
Clarifai	contractor	0.05
Clarifai	fine-looking	0.048
Clarifai	skillful	0.044
Clarifai	pretty	0.039
Google	Beauty	0.06

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