Race and Gender Disparities in Academic Pay

Peter Choi & Erick Axxe

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Acknowledgements

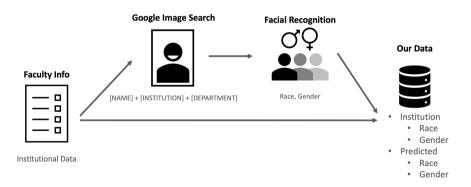
- Academic Analytics Data
- Ohio State Sociology Department's Small Grants Fund
- Research Assistants: Christopher Lindsay, Godwin Mshiu, Melina Raglin, Xiaowen Sun, Yulu Qin

Part I. Facial Recognition & Validation

Facial Recognition?

- Rise of Big Data -> abundance in data
- Less utilization in research due to lack of demographic (race, gender) information
- Facial Recognition can efficiently address this shortcoming
- How well do these work? Can we use it for research?

Framework



Algorithm

Computer Vision

deep learning technique that analyzes multiple layers of an image to associate patterns between its content and a user-generated variable

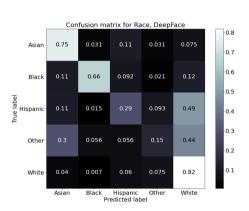
Two Models

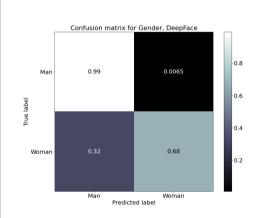
- Deepface: face recognition and facial attribute analysis model
- age, gender, emotion, and race (7 category)
- 2 Fairface: Model that specifically focuses on reducing bias in training data (overrepresentation of Whites, underrepresentation of minorities)
- age, gender, race (7 category/4category)

Validation Data

			Race			
	Institution Race		Deepface Race		Fairface Race	
White	3791	68.8%	1823	61.2%	2679	68.3%
Asian	966	17.5%	568	19.1%	674	17.2%
Hispanic	372	6.8%	258	8.7%	204	5.2%
Black	307	5.6%	131	4.4%	175	4.5%
Other	74	1.3%	199	6.7%	193	4.9%
Total	5510	100.0%	2979	100.0%	3925	100.0%
			Gender			
	Institution Gender		Deepface Gender		Fairface Gender	
Man	2917	62.6%	2268	76.1%	2474	63.4%
Woman	1743	37.4%	711	23.9%	1431	36.6%
Total	4660	100.0%	2979	100.0%	3905	100.0%

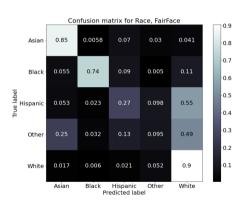
Validation Results - Deepface

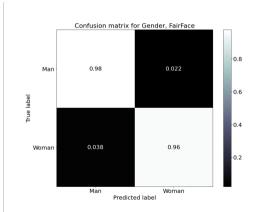




Part I. Facial Recognition & Validation 0000000000

Validation Results - Fairface





Validation Results - Summary

Race

Model	Race	Precision	Recall	F1
	Asian	76.41%	75.35%	75.87%
	Black	70.99%	65.96%	68.38%
DeepFace	Hispanic	22.87%	28.92%	25.54%
	Other	4.02%	14.81%	6.32%
	White	89.91%	81.79%	85.65%
	Asian	87.24%	85.34%	86.28%
	Black	84.00%	73.87%	78.61%
Fairface	Hispanic	35.78%	27.44%	31.06%
	Other	3.11%	9.52%	4.69%
	White	91.43%	90.44%	90.93%

<u>Gender</u>

Model	Race	Precision	Recall	F1	
D	Men	85.87%	99.35%	92.12%	
DeepFace	Women	98.13%	67.52%	80.00%	
F-1-f-	Men	97.97%	97.77%	97.87%	
Fairface	Women	95.81%	96.17%	95.99%	

Conclusion

- Fairface predicts Asians, Blacks, and Whites better than Hispanics and 'Others'
- \blacksquare Accuracy for gender is over 95% when using Fairface (DeepFace ${\sim}86\%)$
- Fairface performs better than Deepface on both race and gender

Q&A

Please ask any questions you may have!

Part II. Race & Gender Disparities in Academic Pay

The New Hork Times

5 Professors Sue Rutgers, Saying It Shortchanges Women on Pay

The five women say they are paid tens of thousands of dollars less than men with similar qualifications. The university says it is "committed to pay equity."



Literature

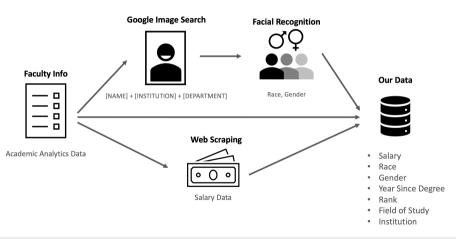
- Existing literature on gender and racial pay gap focus on allocative, valuative, and within-job discrimination (Peterson and Morgan 1995; Dwyer 2013; Glenn 1992; Pager, Bonikowski, and Western 2009)
- Literature on **Academic wage** also focus on race and gender (Chen and Crown 2019; Renzulli et al. 2013; Toutkoushian, Bellas, and Moore 2007)
- But most of these studies require restricted data, nationally representative sample, or are limited to certain institutions
- To overcome this limitation, we extract race & gender using **computational methods** to examine inequality in faculty pay

Our Research

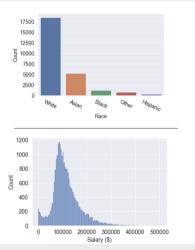
Are there disparities in Academic pay by Race and Gender?

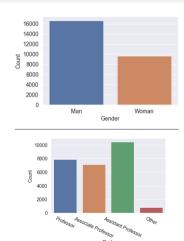
- 119 universities and colleges in the US
- 12 subject areas
- 25,586 faculty members
- 2018 Salary

Data Processing Method



Data





Rank

Peter Choi & Erick Axxe

Method

- Linear Mixed-Effects Model
- Random Intercepts
 - Field of Study
 - Institution
- Intersectional Analysis (by race and gender)

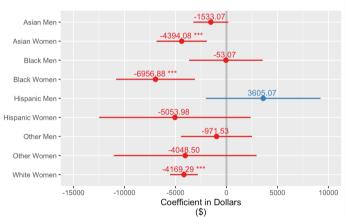
Linear Mixed-Effects Model

	Total Salary for 2018					
	Model 1	Model 2	Model 3	Model 4	${\it Model}\ 5$	
Asian	-9,912***	-10,319***	-9,303***	-1,157	-1,411	
Black	-7,409***	-7,049***	-6,781***	-1,331	-1,295	
Hispanic	-2,417	-2,539	-2,216	1,987	1,962	
Other	-6,423***	-8,294***	-7,738***	-749	-833	
Woman		$-11,\!485^{***}$	$-10,\!948^{***}$	$-4,\!116^{***}$	$-4,\!204^{***}$	
Year since Degree			-170***		95***	
Associate Professor				-32,602***	-33,552**	
Assistant Professor				-50,860***	-52,575***	
Other				-83,268***	-81,667***	
Constant	113,874***	118,581***	457,258***	145,151***	-43,213	

p < .05; p < .01; ***p < .001

Base categories for race, gender, and rank are white, man, and professor.

Intersectional Salary Gap Compared to White Men



*Includes random intercepts for field of study and institution, and controls for professorial rank.

Conclusion

- There is a significant **gender gap (\$4,204)** for female faculty, after controlling for rank, and year since terminal degree
- Racial differences are no longer significant once we control for professorial rank
- Intersectional analysis results show that Asian, Black and White Women are being paid significantly less than White men

Q&A

Please ask any questions you may have!

Part III: DCiFR

DCiFR

DCiFR (Demographic Characteristics in Facial Recognition) is a user-friendly GUI developed by our team

- allows you to run complex deep learning models without any programming skills
- simply choose the picture you want to analyze and get results
- Main author: Melina Raglin

Demo

https://github.com/mlraglin/DCiFR

Q&A

Please ask any questions you may have!

Thank you

- Peter Choi
 - choi.1443@osu.edu
 - @eungang_choi
 - https://www.eungangchoi.com
- Erick Axxe
 - axxe.1@osu.edu
 - @ErickAxxe
 - https://axxe.netlify.app

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