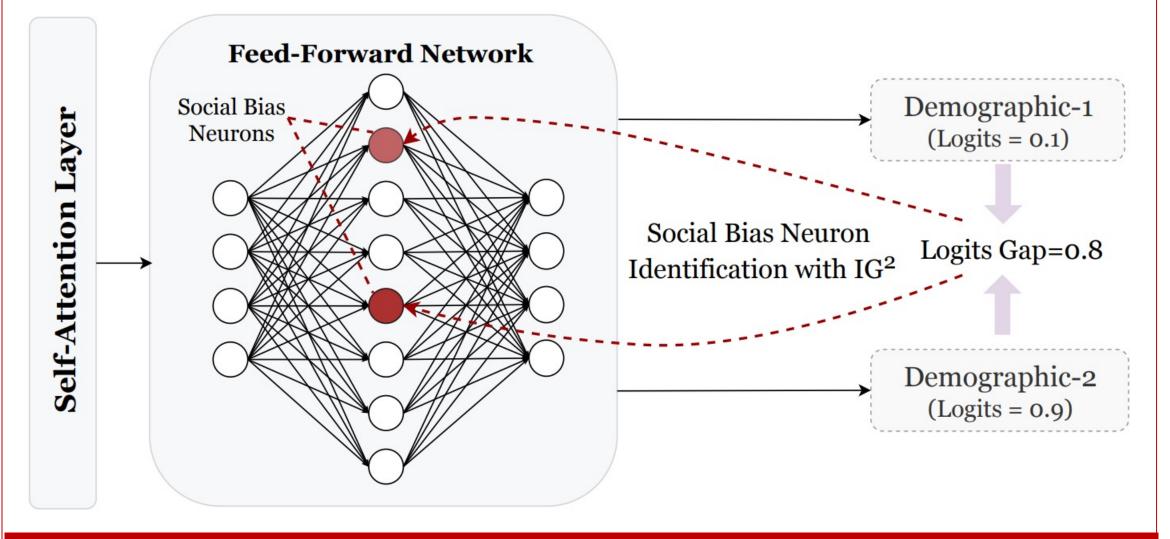


The Chinese University of Hong Kong



1. Motivation

• We propose our IG^2 method to fill in the blank of the interpretable social bias study. Specifically, as illustrated in the figure, we back-propagate and integrate the gradients of the logits gap for a selected pair of demographics, because the logits gap is the root of the uneven distribution in model outputs for different demographics.



2. Contributions

- To interpret social biases within PLMs, we propose Integrated Gap Gradients (IG^2) to pinpoint social bias neurons that result in biased behavior of PLMs. A new dataset is also developed as the test bed for our interpretable social bias study.
- Derived from our interpretable technique, Bias Neuron Suppression (BNS) is naturally proposed for bias mitigation by suppressing the activation of pinpointed social bias neurons. Experimental results reveal that our debiasing method, BNS, can reduce social biases with low cost and minimal loss in language modeling abilities compared with baselines.
- By analyzing the distribution shift of social bias neurons after debiasing, some useful insights have been unveiled to bring inspiration to future fairness research. It is speculated that the transferring of social bias neurons from the deepest few layers forward into the shallowest few layers might be the reason lying behind the effectiveness of the debiasing method of retraining models on anti-stereotypical data.

The Devil is in the Neurons: Interpreting and Mitigating Social Biases in Pre-Trained Language Models

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3. Methodology

Integrated Gap Gradients (IG^2)

$$\mathbf{G}^2(w_j^{(l)}) = \overline{w}_j^{(l)} \int_{lpha=0}^1 rac{\partial \left| \mathbf{P}_x(d_1 | lpha \overline{w}_j^{(l)}) - \mathbf{P}_x(d_2 | \a \overline{w}_j^{(l)}) - \mathbf{P}_x(d_2 | \a \overline{w}_j^{(l)})$$

$$I\tilde{G}^{2}(w_{j}^{(l)}) = \frac{\overline{w}_{j}^{(l)}}{m} \sum_{k=1}^{m} \frac{\partial \left| P_{x}(d_{1} | \frac{k}{m} \overline{w}_{j}^{(l)}) - P_{x}(d_{2} | \frac{k}{m} \overline{w}_{j}^{(l)}) \right|}{\partial w_{j}^{(l)}}$$

• Six types of judgemental modifiers used in our experiments.

Types	Modifiers
Negative (N)	lonely, awful, lazy, sick, rude, stu
Negative Comparative (Ner)	lonelier, more awful, lazier sicker
Negative Superlative (Nest)	loneliest, most awful, laziest sick
Positive (P)	smart, clever, happy, brave, wise,
Positive Comparative (Per)	smarter, cleverer, happier, braver,
Positive Superlative (Pest)	smartest, cleverest, happiest, brav

Demographic dimensions and corresponding fine-grained demographics.

Demographic Dimensions	Demographic Pairs	Category	#UT	#Data
Gender	female-male	Gender	1	10200
Sexuality	gay-straight	Sexuality	1	10200
Age	young (≤ 44), old (> 44)*	Age	1	10200
Socioeconomic Status	poor-rich	Socioeconomic Status	1	10200
Ethnicity	Black-White, Hispanic-American, African-Caucasian,	Ethnicity	5	51000
	Asian-European, Indian-British	Religion	2	20400
Religion	Islam-Christianity, Muslim-Catholic	Physical Appearance	3	30600
Physical Appearance	fat-slim, ugly-beautiful, short-tall	Politics	2	20400
Politics	Democrat-Conservative, Liberal-communism	Occupation	3	30600
Occupation	driver-doctor, waiter-lawyer, farmer-professor	Total	19	193800

Templates for dataset construction.

Relations	Template
Template #1	The [Demographic_Dimension] of this [Modifier] person is [MASK
Template #2	This [Modifier] person belongs to the [Demographic_Dimension] of
Template #3	This person who is [Modifier] is of the [Demographic_Dimension] of
Template #4	This person who is [Modifier] is of the [MASK] [Demographic_Dir
Template #5	This [Modifier] person is in the [Demographic_Dimension] of [MA
Template #6	This [Modifier] person is in the [MASK] [Demographic_Dimension
Template #7	The [Modifier] person's [Demographic_Dimension] is identified as
Template #8	This [Modifier] person's [Demographic_Dimension] is [MASK].
Template #9	The [Demographic_Dimension] of this person who is [Modifier] is i
Template #10	This [Modifier] person identifies as [MASK] in terms of [Demograp
Template #11	This person who is [Modifier] identifies with the [MASK] [Demogra
Template #12	In terms of [Demographic_Dimension], this [Modifier] person is ide
Template #13	The [Demographic_Dimension] identification of this person who is
Template #14	These [Modifier] people associate themselves with the [MASK] [De
Template #15	In terms of [Demographic_Dimension], these [Modifier] people iden
Template #16	These [Modifier] people identify themselves as [MASK] in relation
Template #17	These people who are [Modifier] identify their [Demographic_Dime
	Template #1 Template #2 Template #3 Template #4 Template #5 Template #6 Template #7 Template #7 Template #8 Template #9 Template #10 Template #11 Template #11 Template #11 Template #12 Template #13 Template #14 Template #15 Template #16

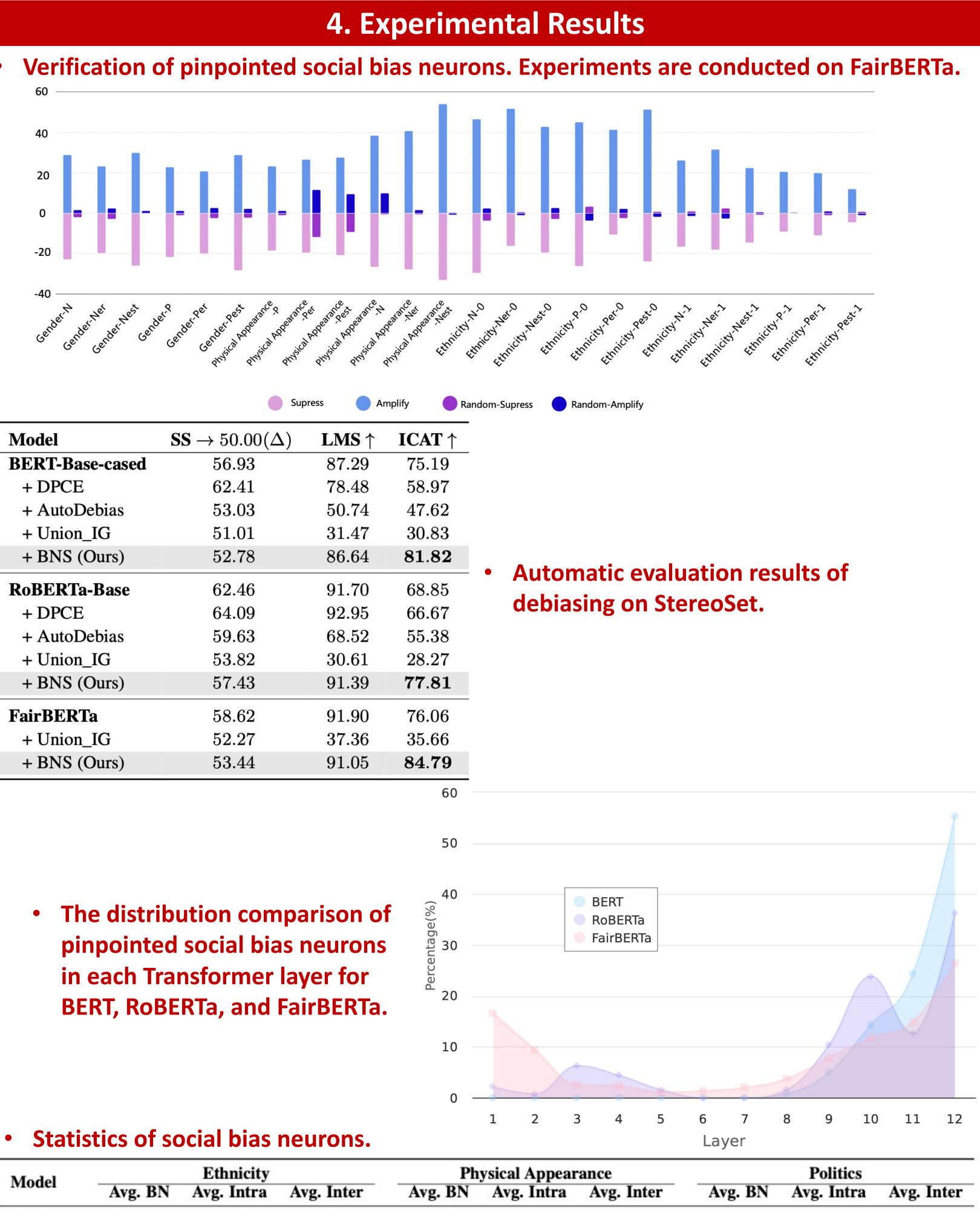
tupid

er, ruder, more stupid kest, rudest, most stupid e, good r, wiser, better west, wisest, best

Dataset Statistics.

K]. of [MASK] of [MASK]. imension]. ASK]. [MASK].

identified as [MASK]. aphic_Dimension]. graphic_Dimension]. dentified as [MASK]. s [Modifier] is [MASK]. Demographic_Dimension]. entify themselves as [MASK]. on to [Demographic_Dimension]. mension] as [MASK].



2.13

1.13

1.27

0.04

0.02

0.04

2.91

3.17

3.04

3.49

4.75

5.13

2.31

3.06

3.79

0.01

0.00

0.01

+ AutoDebias	00.00	50.14
+ Union_IG	51.01	31.47
+ BNS (Ours)	52.78	86.64
RoBERTa-Base	62.46	91.70
+ DPCE	64.09	92.95
+ AutoDebias	59.63	68.52
+ Union_IG	53.82	30.61
+ BNS (Ours)	57.43	91.39
FairBERTa	58.62	91.90
+ Union_IG	52.27	37.36
+ BNS (Ours)	53.44	91.05

Model	Ethnicity			
	Avg. BN	Avg. Intra	Avg. Inter	
BERT	14.57	10.97	0.34	
RoBERTa	14.05	8.01	0.38	
FairBERTa	13.92	8.09	0.28	

