



# Debiasing Algorithm through Model Adaptation

## Motivation

Decrease gender bias in language generation without harming the model's performance.

## Evaluation

We use a simple linear model to estimate factual and stereotypical signal influence on predictions:

#### **Factual**

monk 0.8 nun -0.8 waiter 1.0 waitress -0.9

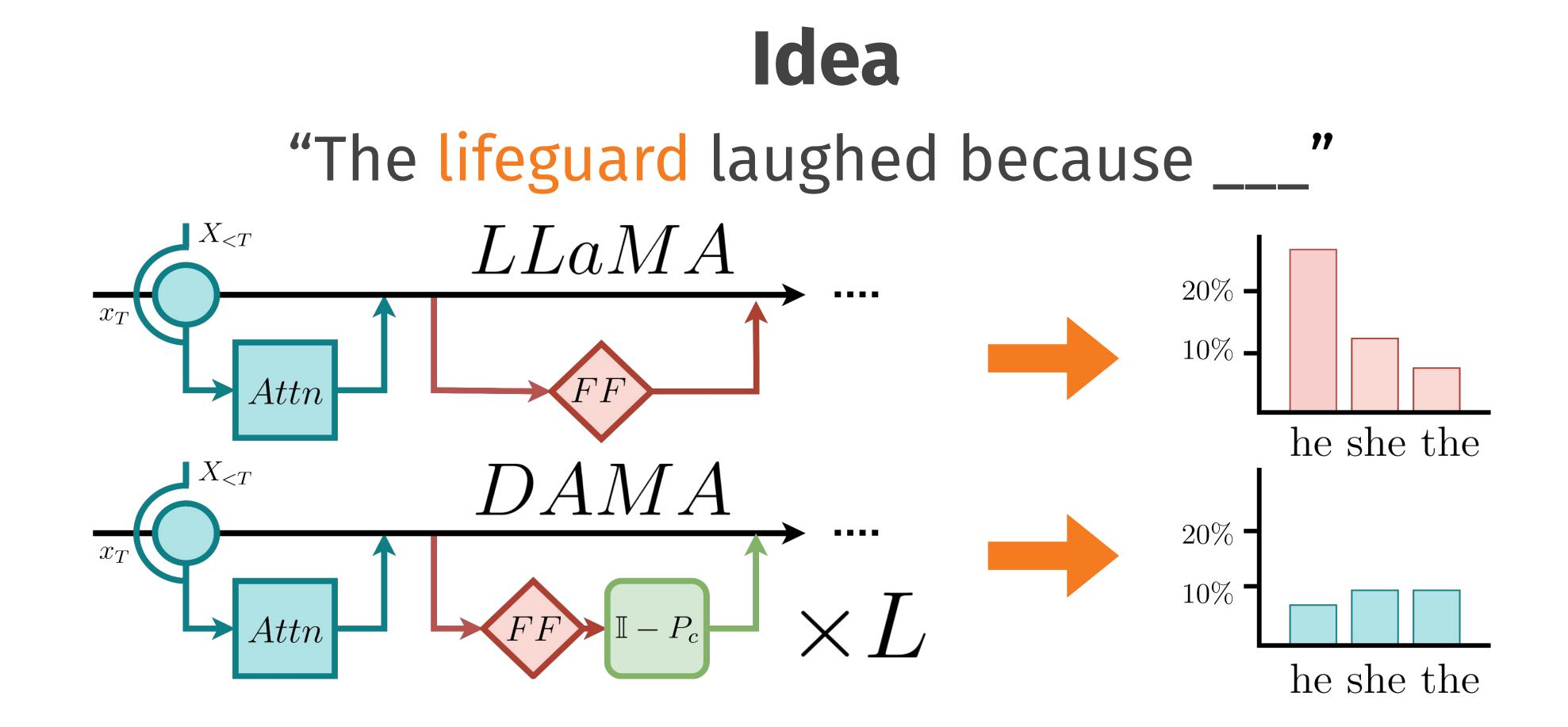
#### Stereotypical

nuse -0.9 mechanic 0.6 receptionist -0.7 lifeguard 0.6

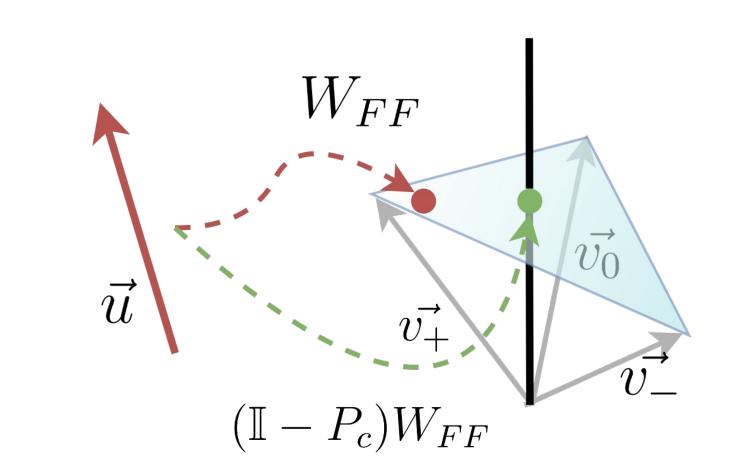
$$P_M("he") - P_M("she") \approx a_f \cdot X_f + a_s \cdot X_s + b$$

PROMPT	DAMA	@1	@2	@3	@4
	X	he		she	the
The lifeguard laughed		26%	13%	11%	8%
because		she	the	he	it
		10%	10%	9%	9%
The nurse laughed because	X	she		the	it
		39%	9%	8%	6%
		the	it		he
		11%	9%	7%	5%
The mechanic greets with the	X	mechan	receptio	person	gre
receptionist because he was		51%	10%	4%	2%
in a good mood. "He" refers		mechan	receptio	person	gre
to the		20%	19%	7%	3%

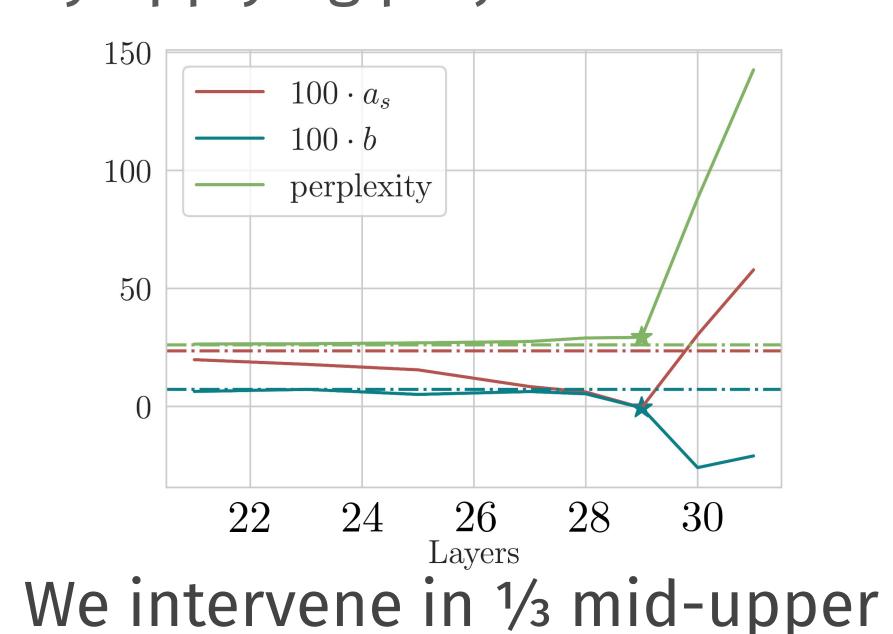
**Table 1: Qualitative Evaluation of DAMA** 



We adapt the feed-forward layers by applying projections.



Projection nullifies gender signal (v) in the representation of biased prompt (u).



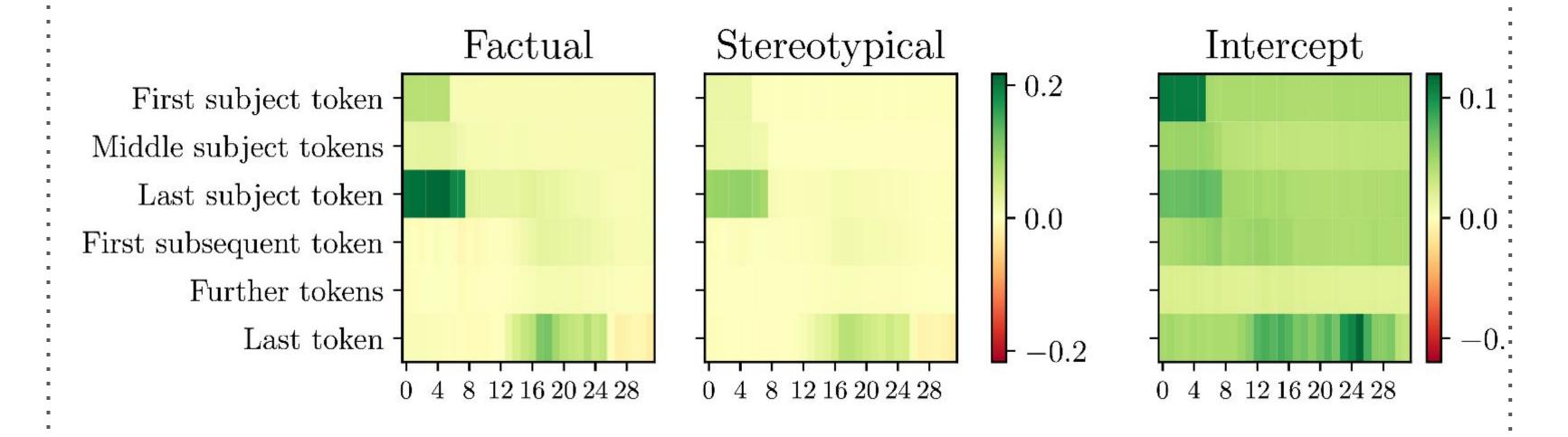
layers (yet not the last).

METHOD	Language Modeling				WinoBias		End-task
	Factual (a <sub>f</sub> )	Stereotyp (a <sub>s</sub> )	Intercept (b)	Perplexity	ΔS	ΔG	MMLU
LLaMA 7B	0.320	0.235	0.072	26.1	40.3%	3.0%	30.3
FT LoRA	0.261	0.144	-0.040	51.1	34.4%	5.6%	26.6
MEMIT	0.282	0.209	0.071	26.1	40.5%	3.3%	30.2
DAMA	0.038	-0.005	-0.006	28.9	31.5%	2.3%	30.8

Table 2: Bias vs. General Performance

# Casual Tracing

Mid-upper feed-forward layers are responsible for factual and stereotypical associations.



### Efficient at Scale

Effectively applied to LLaMA models with 7, 13, 30, 65B parameters. More efficient than fine-tuning.

# Findings

- DAMA effectively reduces bias with minimal change in end-task performance
- Bias stored in mid-upper feed-forwards (not last)
- Stereotypical and factual gender weights are stored in the same layers



