Task Vectors as semantic sliders for text generation

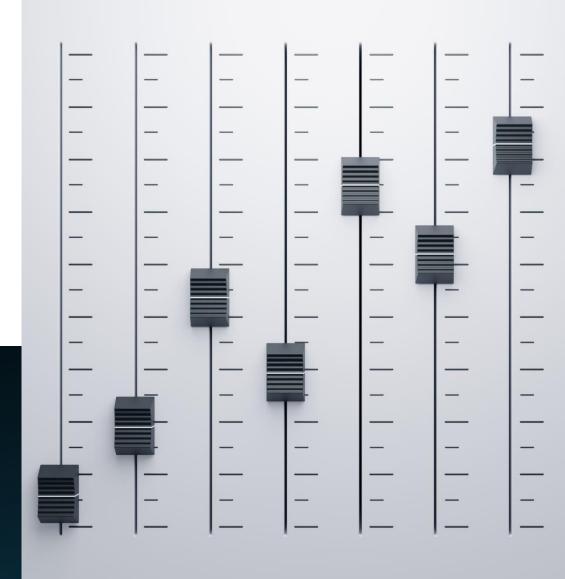
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Introduction

Research Questions

- Can we control the level of toxicity in a text generated by a GPT-2 small model using a single task vector?
- How can we navigate a generated vector space defined by one gender- and one racetask vector, and what constraints limit movement within this space?

Background

Current Techniques

- **Prompt engineering**: Requires manual tuning
- Adapters & LoRA: Need retraining and architectural changes

Background

Task Vectors: A Lightweight Alternative

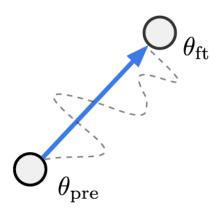
- Directly operate in the model's parameter space
- Represent directional shifts in learned behavior
- Do **not** require retraining or architecture changes
- Offer an interpretable, modular way to guide model outputs

Data

- Replication experiment
 - 2000 civil comments
- Second experiment
 - 2000 civil comments categorized as female
 - 2000 civil comments categorized as *black*

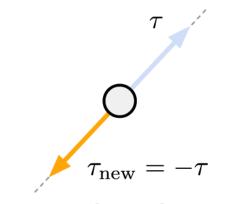
Methodology

a) Task vectors



$$\tau = \theta_{\rm ft} - \theta_{\rm pre}$$

b) Forgetting via negation



Example: making a language model produce less toxic content

c) Learning via addition

$$au_{\text{new}} = au_A + au_B$$

$$au_A au_B$$

Example: building a multi-task model

d) Task analogies

$$au_{
m new} = au_C + (au_B - au_A)$$
 au_B
 au_C

Example: improving domain generalization

One Vector: $\theta new = \theta pre + \lambda$ • T

Two combined Vectors: Tnew = TA + TB

Base-model

GPT-2

- Trained on ~8M web pages, 117M parameters
- **Decoder-only** model
- Strong benchmark performance despite size
- Used in this study for **finetuning**, **generation** and **evaluation**

Experimental setup

- •GPT-2 small and toxic data for finetuning
- Saved pretrained & finetuned weights
- •Created task vectors by scaling differences (-1 to 1, step 0.1 → 20 models)
- •Generate text with prompt "you're a real".

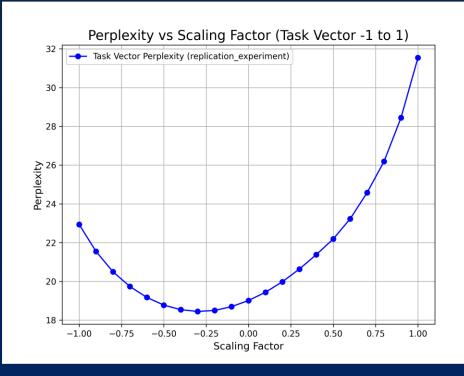
Evaluation metrics

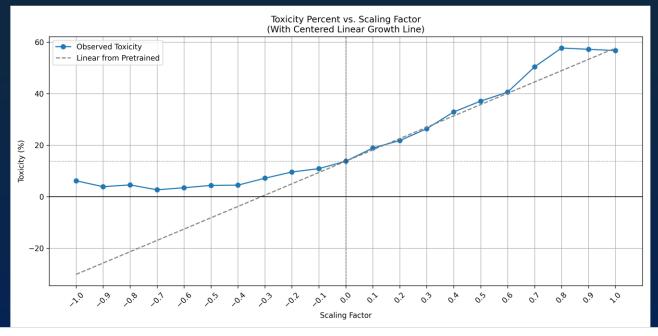
- Perplexity
- Detoxify
- LLM-as-a-judge

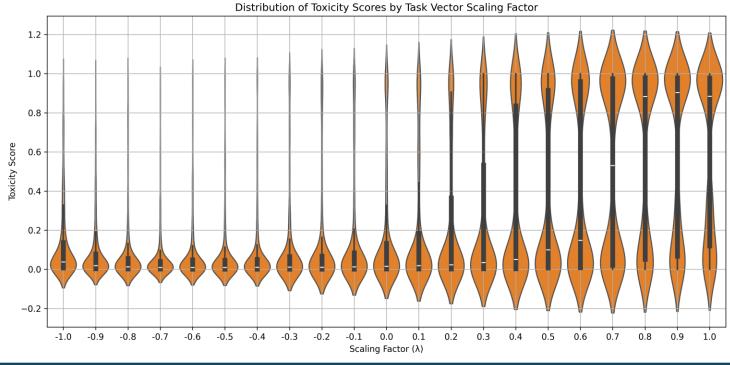
Expected results

- Near-linear changes in toxicity
- Predictable semantic shifts
- Additive and composable effects

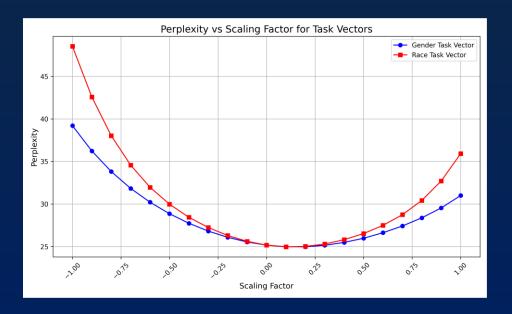
Results, Replication

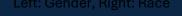


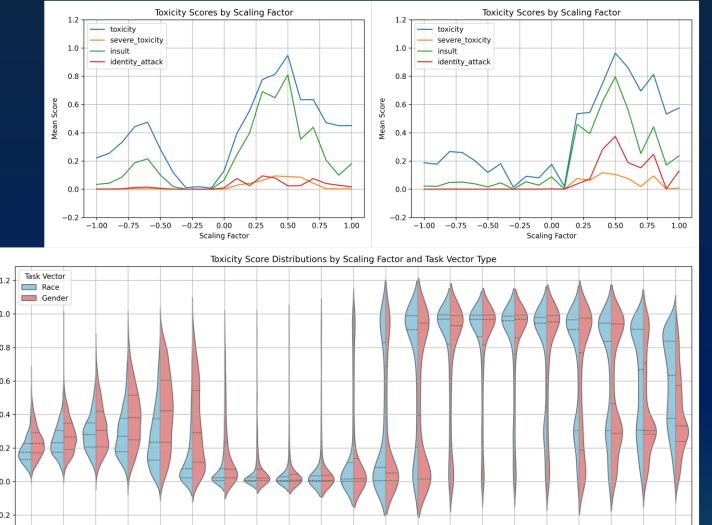




Results, Further experiments







0.0

Scaling Factor (λ)

0.1

0.7

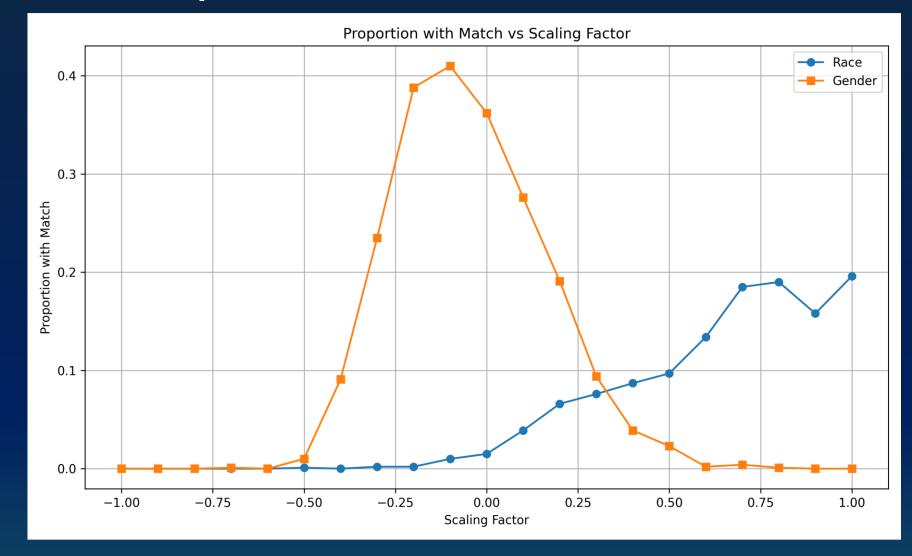
0.8

-0.5

-0.4

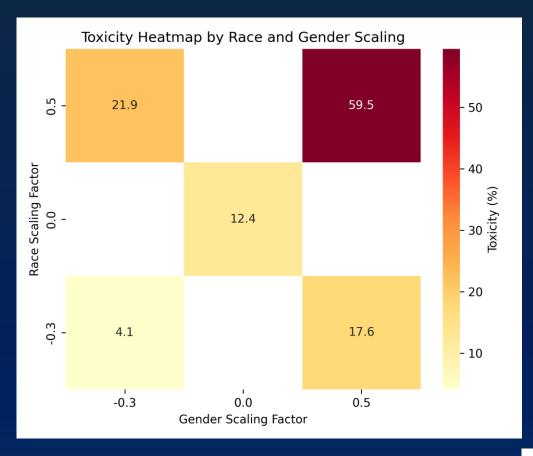
-0.3

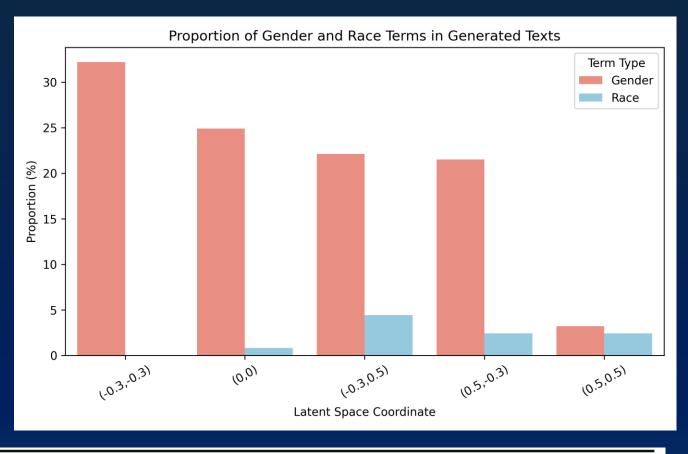
Results, Further experiments



Proportion of 1,000 samples that include at least one matched term using a case-insensitive regular expression.

Results, Further experiments





Gender/Race Term	(0,0)	(-0.3,-0.3)	(0.5,0.5)	(0.5,-0.3)	(-0.3,0.5)
Gender	24.9%	32.2%	3.2%	21.5%	22.1%
Race	0.8%	0.0%	2.4%	2.4%	4.4%

Conclusions

Research Question 1

Can we control toxicity using a single task vector?

- \rightarrow **Yes.** Increasing the scaling factor raised toxicity levels in GPT-2 small outputs.
- The effect was **non-linear**, plateauing at higher values.
- Perplexity remained stable at moderate scales suggesting a "sweet spot" for control without sacrificing fluency.

Research Question 2

How do gender and race task vectors interact in vector space?

- → Partially additive effects.
- Combining vectors enabled dual control across identity axes.
- Interactions were **not always linear or symmetric**, with some combinations producing **unexpected effects**.
- Suggests a navigable but constrained vector space with complex dynamics.

Key Takeaways

- Task vectors allow meaningful, interpretable control over LLM output.
- Compositionality is possible, but subject to model-specific constraints.
- Future work should explore:
 - More granular control dimensions
 - Generalization across tasks, datasets, and architectures.

Thank you!