

# LLM Induced Embedding Spaces

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**The aim of this project** is to investigate the embedding spaces induced by LLMs. Below are different ways to approach this problem.

## INVESTIGATE AND MODIFY SPACE

Investigating an embedding space present some difficulties, as the spaces consist of multidimensional vectors which encode information.

**Dar et al. (2023)** treat each layer output as the final output of the model and decode the embeddings using an inverse of the first layer embedder.

**Tennenholtz et al. (2023)** investigate a target embedding space by creating an adapter to input target embeddings to separate LLM and querying its properties using natural language.

These findings show that **mapping from an embedding space to a vocabulary space** is achievable and **interpolating** between two points in the embedding space yields semantically meaningful outputs.

**Liu et al. (2023)** create task specific vectors to steer the model layer outputs, effectively turning few-shot prompting to one query by modifying the model's latent space.

**Li et al. (2023)** linearly interpolate each attention head in a model to steer the model output to a more desired direction.

Turner et al.  
2024

These results pave the way to **modifying the embedding space** in a purposeful way.

Penedo et al.  
2023

## PROPERTIES

Timkey et al.  
2021

Statistical analysis of word representations has shown that embedding spaces of popular LMs are highly anisotropic.

Li et al.  
2020

Thus, cosine similarity as a metric has been questioned.

Subramani et al.  
2022

Focus has mostly been on how to combat this issue.

Steck et al.  
2024

Mickus et al.  
2020

There's been an uptick in research about how training data affects model downstream performance.

Ostendorff et al.  
2024

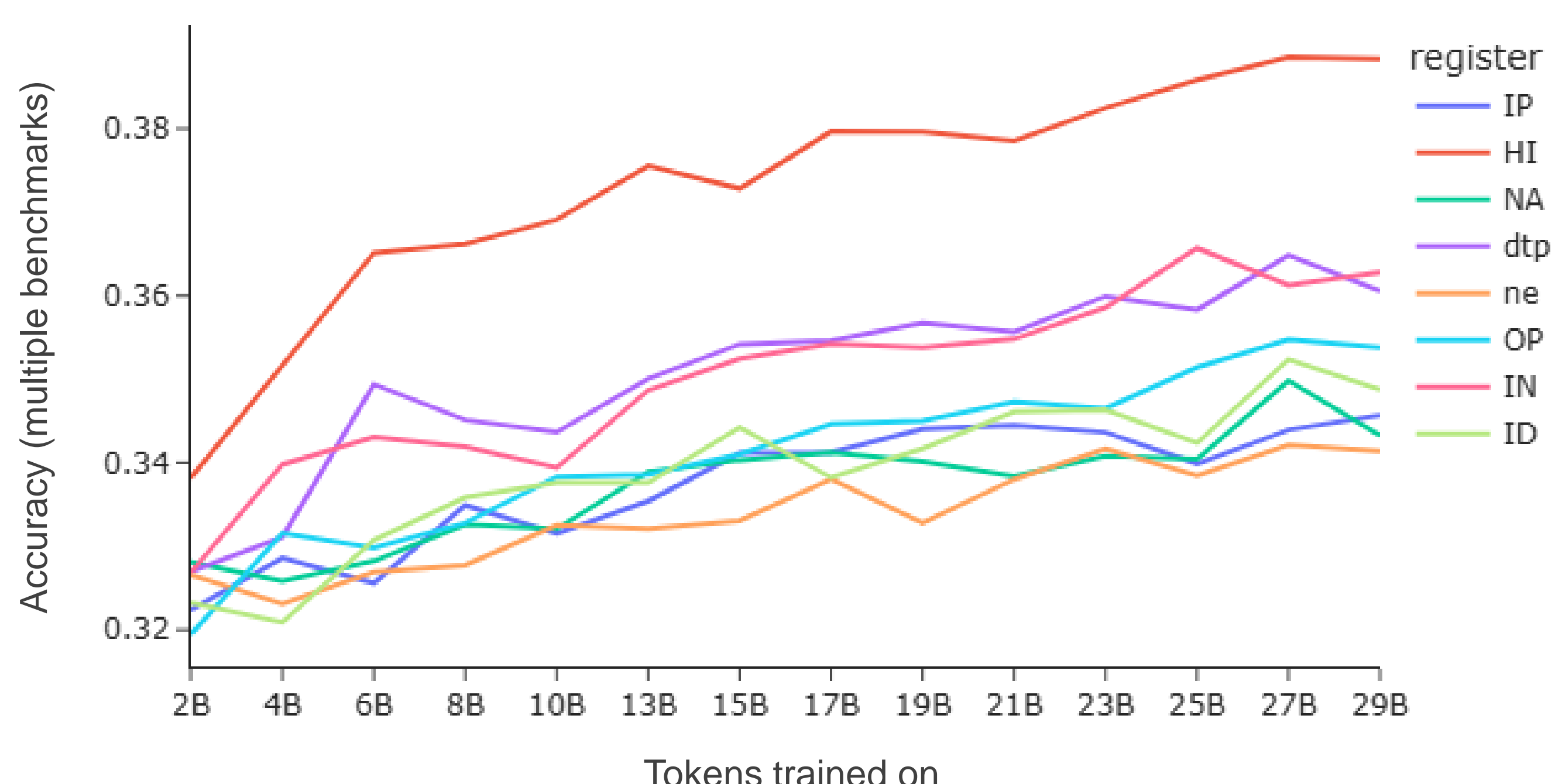
Generally, this research is focused on statistical text metrics, with some exceptions, and the goal is to maximize benchmark performance.

This opens up questions about the effect of training data on the embedding space and about the qualities that correlate with model performance.

Longpre et al.  
2024

## MODEL TRAINING

**Current work** is focused on the effect of training data on LLMs. Following Penedo et al. (2024), I train multiple LLMs with different datasets, filtered with linguistic criteria: by register (text genre). Figure below presents preliminary findings.



The models trained and evaluated in this first publication can be used later to analyse the qualities of embedding spaces that are affected by linguistic features of training data.

**Research Questions** for this project are

**RQ1**

Can you build a system to get the sense of semantic meaning for an arbitrary point in an embedding space?

**RQ2**

What happens in the neighbourhood of an arbitrary point and what effects steering has?

**RQ3**

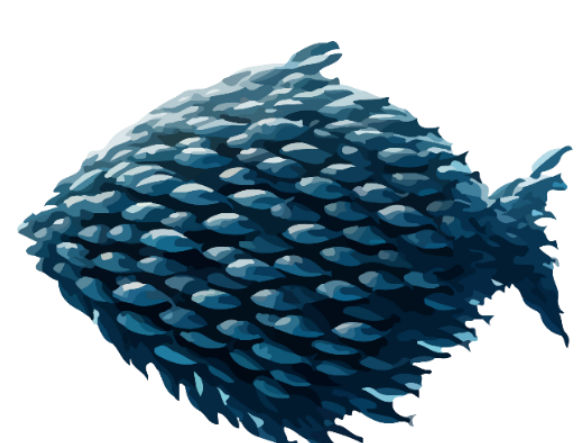
How can we affect the space using the training data of the model and are there qualities of the space that correlate with model performance?



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