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 a. (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.

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

Subramani et al. 2022

Turner et al. 2024

PROPERTIES

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

Thus, cosine similarity as a metric has been questioned.

Focus has mostly been on how to combat this issue.

Timkey et al. 2021

Li et al. 2020

Steck et al. 2024

Mickus et al. 2020

MODEL TRAINING

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

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.

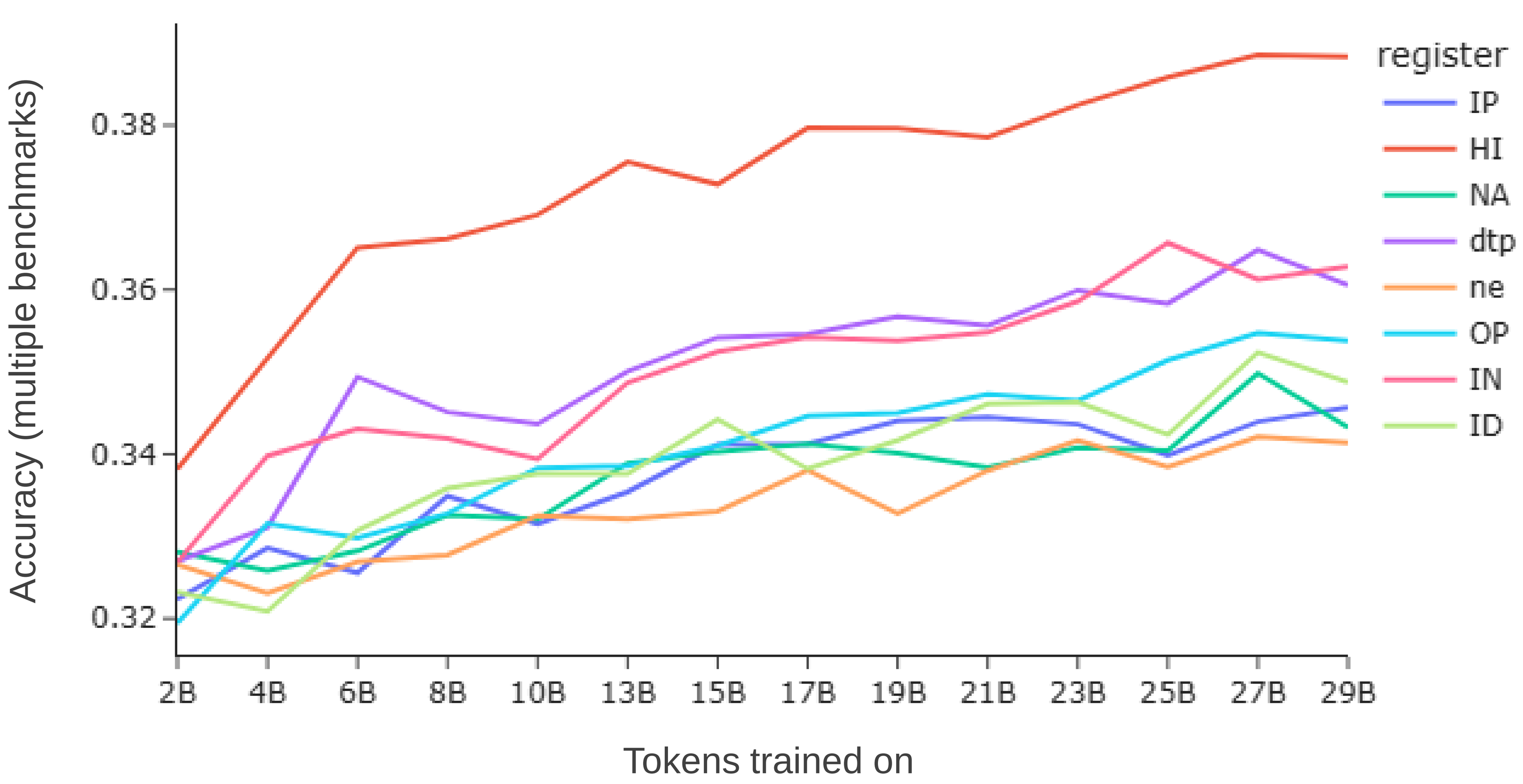
Ostendorff et al. 2024

Penedo et al. 2023

Longpre et al. 2024

Current work

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

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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