STEERING LANGUAGE MODELS WITH ACTIVATION ENGINEERING

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ABSTRACT

Prompt engineering and finetuning aim to maximize language model performance on a given metric (like toxicity reduction). However, these methods do not fully elicit a model's capabilities. To reduce this gap, we introduce a form of *activation engineering*: the inference-time modification of activations in order to control (or *steer*) model outputs. Specifically, we introduce the *Activation Addition* (ActAdd) technique, which contrasts the intermediate activations on prompt pairs (such as "Love" versus "Hate") to compute a *steering vector* (Subramani et al., 2022). By tactically adding in e.g. the "Love" − "Hate" steering vector during the forward pass, we achieve SOTA on negative-to-positive sentiment shift and detoxification using models including LLaMA-3 and OPT. ActAdd yields inference-time control over high-level output properties (like topic and sentiment) while preserving performance on off-target tasks. ActAdd is lightweight: it does not require any machine optimization and works with a single pair of data points, which enables rapid iteration over steering. ActAdd demonstrates the power of activation engineering.

1 INTRODUCTION

LLMs contain hidden capabilities we do not know how to fully elicit (Korinek, 2023). Naively prompting a model with a question does not maximize the probability of the correct response. For example, consider how prompting a model to think "step-by-step" (Wei et al., 2022) massively improves performance on a range of benchmarks. Similarly, "few-shot" prompting a model with correct answers to unrelated in-distribution questions allows "in-context learning" for e.g. stronger performance on NLP tasks (Brown et al., 2020). Importantly, these interventions do not supply the LLM with extra task-relevant information or update the algorithm implemented by the LLM's computational graph. Even though the model is initially *able* to score higher on these benchmarks, those capabilities do not emerge without a specific intervention. We therefore hypothesize an *elicitation overhang*: we do not know how to elicit all relevant abilities and information from models.

Prompt engineering is the most obvious way to steer a model, but prompting has limited reliability (Ye & Durrett, 2022; Wang et al., 2024). Therefore, to reduce the elicitation overhang, we explore a new modality for steering language model outputs. By strategically perturbing activations during the forward pass, we hope to more reliably and effectively steer models compared to prompt engineering. This is a form of*activation engineering*.

We suspect that compared to prompt engineering, activation engineering can elicit a wider range of model capabilities. Consider, for example, a model optimized to imitate the text outputs of eloquent poets and awkward mathematicians. The model may contain the internal mechanisms required to output text which is *both* eloquent and mathematical. However, if the model is an accurate estimator of the training distribution, it will (correctly) assign low probability to eloquent mathematical prose. Because nothing in the training data was both eloquent and mathematical, there may exist no prompt which elicits mathematical prose. In contrast, activation engineering might be able to simultaneously activate the circuitry for eloquent speech and for mathematical content.

To demonstrate the power of activation engineering, we introduce *Activation Addition* (ActAdd). Suppose we want to achieve negative-to-positive sentiment control (Li et al., 2018; Dathathri et al., 2020). To achieve this, ActAdd first compares the model's activations on a contrast pair of prompts, such as the prompts "Love" and "Hate." The otherwise-similar prompts differ along the target dimension of sentiment. ActAdd then computes the difference of these activations in order to

compute *steering vectors*. These vectors act like "virtual bias terms" because ActAdd *directly adds* the steering vectors to the forward pass at inference time. By shifting the inference-time activations along the direction of the steering vector, ActAdd steers the model towards text with the vector's meaning (Table 1).

Table 1: The impact of ActAdd. The steering vectors are computed from ("Love" - "Hate") and ("I talk about weddings constantly" - "I do not talk about weddings constantly"). Appendix Table 6 shows more examples.

Prompt	+ **steering**	= **completion**
I hate you because...	[None]	...you are the most disgusting thing I have ever seen.
	ActAdd (love)	...you are so beautiful and I want to be with you forever.
I went up to my friend and said...	[None]	..."I'm sorry, I can't help you." "No," he said. "You're not."
	ActAdd (weddings)	..."I'm going to talk about the wedding in this episode of Wedding Season. I think it's a really good episode. It's about how you're supposed to talk about weddings."

Contributions. We unify past literature on related topics to introduce *activation engineering*. To better elicit the full capabilities of models, we introduce the ActAdd steering method, which achieves SOTA on toxicity reduction and sentiment control. We thoroughly test the steered models to verify the preservation of their general capabilities. We therefore show the promise of ActAdd as an effective and cheap method for steering LLM outputs.

2 Related Work

Latent space arithmetic. Computer vision researchers have long demonstrated the ability to steer image generation using derived vectors, including steering latent variables – most famously, shifting activations along a direction that corresponds to smiling in images (Larsen et al. 2016; White 2016). Similarly, in the text domain, classic results on the word2vec embedding show that arithmetic on word vectors can capture some parts of semantic reasoning (for instance, analogies: Mikolov et al. 2013b;a). Our work focuses on steering generative language models.

LLM steering. Many approaches attempt to affect the output of a pretrained LLM, whether:

- *Intervening on weights*, as with supervised finetuning, RLHF, steerable layers, and weight editing (that is, targeted fine-tuning) (Ranzato et al. 2016; Ziegler et al. 2019; Dathathri et al. 2020; Meng et al. 2023; Ilharco et al. 2023). However, naive RLHF, finetuning, and weight editing have known side-effects on overall model performance (Hase et al. 2023; Qi et al. 2023; Brown et al. 2023);
- *Intervening at decoding*, as with guided or trainable decoding (Gu et al. 2017; Grover et al. 2019; see Zhang et al. 2022a for an overview of controlled generation and Jin et al. 2022 for textual style transfer);
- *Intervening on the prompt*, as with automated prompt engineering (Shin et al. 2020; Zhou et al. 2022);
- *Intervening on token embeddings*, as with 'soft prompting' (Li & Liang 2021; Lester et al. 2021; Khashabi et al. 2022);

- *Intervening on activations*, for instance by freezing the weights of the LLM and searching for a 'steering vector' of activations, e.g. using gradient descent (Subramani et al. 2022; Hernandez et al. 2023). These optimized extraction methods, which search for a steering vector, differ from extraction methods which directly compute it (present work and Li et al. 2023b). In our work, we do not use gradient descent or other optimization methods.

Table 2: Locating our work in the steering literature.

	Vector intervenes on model ...	
Intervention vectors obtained via	*... weights*	*... activations*
Differences after fine-tuning	Ilharco 2023	N/A
Per-query gradient-based search	Meng 2022, Orgad 2023	Dathathri 2020, Subramani 2022, Hernandez 2023
Differences between prompt pairs	N/A	**ActAdd** (present work), Li et al., 2023b

Activation engineering. Activation engineering involves creating vectors of activations which cause desired changes to output text when added to the forward passes of a frozen LLM (Dathathri et al. 2020). Table 2 organizes prior work by intervention type.

An early antecedent is the Plug-and-Play Language Model of Dathathri et al. 2020. This uses a separate classifier (one classifier per attribute to steer towards) to perturb the model's activations to generate text that accords more closely with the classifier's target. Subramani et al. 2022 extract latent steering vectors from a frozen LLM, successfully discovering sentence-specific vectors which steer completions to near-perfect BLEU scores (i.e, control of the LLM's generation) and unsupervised style transfer. However, the method requires running gradient descent for each new steering vector. Hernandez et al. 2023 locate and edit an LLM's knowledge through learning an encoding of facts in its activation space. Ablating attention heads can also be seen as activation engineering, though the technique is mostly used for model interpretation rather than steering (Michel et al. 2019; Olsson et al. 2022).

Independently, Li et al. 2023b developed a similar method (ITI) which computes steering vectors which are selectively applied according to trained linear probes. They use these probes to find attention heads with different activation distributions for true and false statements. They steer the model toward truthful outputs, where our experiments cover a range of goals. In addition, ITI adds the same steering vector at all sequence positions during inference and ITI requires dozens of samples. In contrast, ActAdd we add steering vectors to a subset of sequence positions and require as few as 2 samples. Similar work on 'in-context vectors' also followed ours (Liu et al. 2023). Lastly, Zou et al. 2023's "representation engineering" also followed our work. They develop a range of techniques for deriving steering vectors and for steering models using activation-space edits and optimization. In comparison to Zou et al. 2023, we steer different models (LLaMA-3, OPT, GPT-2, and GPT-J) on different tasks (detoxification and sentiment control).

By contrast, the interpretability technique *activation patching* involves replacing some activations instead of adding a vector (Heimersheim & Nanda 2024). Vig et al., 2020 use a related method, causal mediation analysis to locate the components of a trained model that mediate gender bias.

3 How Activation Addition works

We use decoder-only Transformer neural networks (Vaswani et al. 2017). The LLMs in this work contain a stack of Transformer layers, each consisting of multi-head attention (MHA) and a feedforward network (FFN). We focus on its "residual streams" (Elhage et al. 2021), the sequences $(\mathbf{x}_0, ..., \mathbf{x}_n)$ of intermediate activation vectors processed by each layer. ActAdd manipulates the residual stream

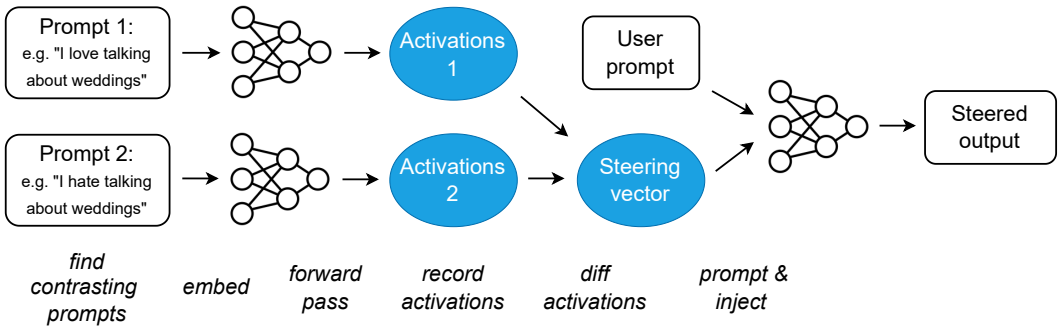


Figure 1: Schematic of the Activation Addition (**ActAdd**) method. ⬭ = natural language text; ● = vectors of activations just before a specified layer. In this example, the output is heavily biased towards discussing weddings, regardless of the topic of the user prompt. (See Algorithm 1 for the method's parameters: intervention strength, intervention layer, and sequence alignment.)

values $\mathbf{h}^l$ input to layer l. Each layer performs MHA and FFN computations on $\mathbf{x}_i$, adding $\mathbf{x}_{i+1}$ to the stream. The final vector $\mathbf{x}_n$ in the stream can then be decoded into the next-token prediction. At inference time, the residual stream is initialized $\mathbf{h}^1$ with the embedding of the tokenized prompt.

Activation addition. Our method takes a pair of natural-language prompts (p_+, p_-), where p_+ represents the property we wish output text to emphasise (e.g. love) and p_- represents its opposite (e.g. hate or indifference). $\mathbf{h}^l_+$ is the activation vector for the prompt p_+ at layer l. The difference $\mathbf{h}^l_+ - \mathbf{h}^l_-$ is a new activation vector which (intuitively) captures the difference between a prompt with the target property, and a prompt without it. The steering vector is computed before inference time.

Algorithm 1 ActAdd, optimization-free activation addition

Input: (p_+, p_-) = steering prompt pair, tokenized
p^* = user prompt
l = target layer
c = injection coefficient
a = sequence position to align $\mathbf{h}_A$ and $\mathbf{h}_{p^*}$
M = pretrained language model
Output: S = steered output

$(p'_+, p'_-) \leftarrow$ `pad_right_same_token_len`(p_+, p_-)
$\mathbf{h}^l_+ \leftarrow M$`.forward`$(p'_+)$`.activations`$[l]$
$\mathbf{h}^l_- \leftarrow M$`.forward`$(p'_-)$`.activations`$[l]$
$\mathbf{h}^l_A \leftarrow \mathbf{h}^l_+ - \mathbf{h}^l_-$
$\mathbf{h}^l \leftarrow M$`.forward`$(p^*)$`.activations`$[l]$
$S \leftarrow M$`.continue_forward`$(c\,\mathbf{h}^l_A + \mathbf{h}^l[a])$

To obtain a steering vector, we perform a forward pass on each prompt, record the activations at the given location in each pass, take the difference $\mathbf{h}^l_+ - \mathbf{h}^l_-$, and then finally rescale this difference in activations by an 'injection coefficient' c. To steer, we add the resulting activation vector to the input of layer l and allow the forward pass to continue, and so obtain our steered output. c represents the intervention strength, since it multiplies the steering vector's contribution to the residual stream.[1] We perform hyperparameter tuning to select c and also the injection layer l. As expected from past work (Subramani et al. 2022; Mini et al. 2023), intervening at the middle layers is most effective. See Appendix C for more details.

Algorithm 1 and Figure 1 depict the resulting ActAdd method. In the appendix, Figure 6 illustrates a figurative example of steering a model with ActAdd if that model had one-dimensional residual

[1]It's typical for the intervention strength c to have a magnitude less than 15.

streams (rather than e.g. GPT-2-XL's 1600 dimensions). A runnable notebook can be found at tinyurl.com/actadd.

We test whether 1) steering vectors are effective at eliciting the desired behavioral shift, and 2) whether they preserve the general capabilities of the model. We run perplexity-based experiments on GPT-2-XL (1.5B parameters, Radford et al. 2019). We then run toxicity and sentiment experiments on OPT (Zhang et al. 2022b) and LLaMA-3 (Meta 2024).

4 Results: Activation Addition works

A summary of all experiments can be found in Table 5.[2]

4.1 ActAdd intuitively modifies next-token probabilities

We consider the OpenWebText corpus (Peterson et al. 2018). Our running example is the "wedding" topic vector produced by setting $p_+ =$ `weddings`, $p_- =$ ' ', $l = 16$, $c = 1$.

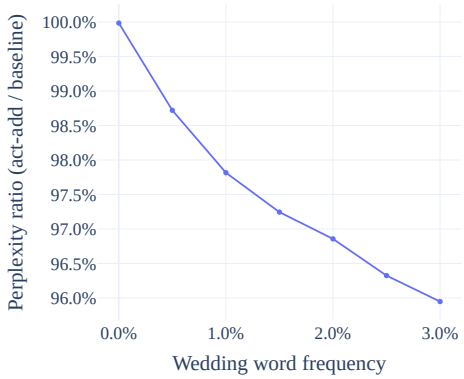
4.1.1 ActAdd reduces perplexity on a target topic

For each document $d_i \in D$ in OpenWebText (Peterson et al. 2018), we first calculate the frequency of wedding-related words.[3] If a document contains one of these words, the document is considered wedding-related. We randomly sample 300k documents, half of which are wedding-related.

We split the documents into sentences and measure GPT-2-XL's perplexity on both the wedding-related and wedding-unrelated sentences. If the model is effectively steered to generate wedding-related text, it should assign that text higher probability (and thus achieve lower perplexity). For more details, see Appendix C.3.

Figure 2 shows the ActAdd perplexity relative to the unmodified model. In sentences where the injected topic (weddings) is more relevant, ActAdd's perplexity is lower and predictive performance increases.

Figure 2: The perplexity ratio compares the relative predictive performance of ActAdd and an unmodified model. Lower is better. Adding the wedding steering vector improves performance on wedding-related text while preserving performance on unrelated text.



4.1.2 ActAdd's impact on token probabilities

To test if the intervention is affecting relevant tokens or reducing perplexity in some spurious way, we observe the shift in the distribution of token log probabilities. We do this by randomly sampling 500 documents from the above OpenWebText sample and recording the log-probabilities assigned by the baseline and steered models. This results in a dataset of about 500k tokens, of which 29k are unique. We then group by token, filter for tokens with >20 instances in the dataset, and calculate the mean perplexity difference between the ActAdd and baseline models. By displaying these as a Q-Q plot (Gnanadesikan & Wilk 1968), we can inspect outlier shifts in token probability.

Appendix Figure 9 shows the resulting mean log-probability difference distribution. We see that is approximately normal for the bulk of the tokens but with clearly heavy tails. The positive tail is significantly heavier than the negative tail, suggesting that one set of tokens are reliably increased in probability, with a smaller set of tokens reliably decreased to a lesser extent. Outlier tokens can be found in Appendix Table 11. *The probabilities most increased on average are primarily wedding-related.* The bottom tokens share no obvious theme and show a significantly lower absolute change in probability.

[2]Code repository for our experiments: `https://zenodo.org/records/14177088`.

[3]`wedding`, `weddings`, `wed`, `marry`, `married`, `marriage`, `bride`, `groom`, and `honeymoon`.

4.1.3 ACTADD STEERS THE MODEL TO DISCUSS WEDDINGS

At what layer are steering vectors most effective? Sweeping over GPT-2-XL injection layers for the wedding vector, we measure the average count of wedding-related words given a steering vector injected at each layer.

The intervention is already effective at the very first layer, rises in effectiveness until layer 6, and then declines. For the optimal injection site, we see >90% success in topic steering (compared to a ∼2% baseline). Figure 3 shows the results of the layer sweep.

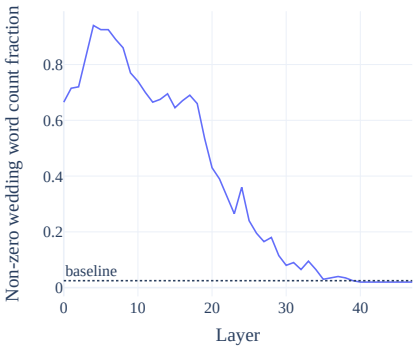


Figure 3: P(steered completion contains wedding-related words) as a function of injection layer; i.e. the fraction of completions that contain at least one of the hand-picked words wedding, weddings, wed, marry, married, marriage, bride, groom, and honeymoon.

4.2 ACTADD CAN CONTROL WHAT THE MODEL TALKS ABOUT

Method. Steering vectors can elicit generations on a range of topics – not just weddings. Starting from a generic prompt, we use GPT-4o-mini to score whether the generations are about a target topic. Specifically, we generate 1000 completions from the unsteered model and 1000 for each target single-token ActAdd intervention (where each token is about a different topic). Compared to the baseline generations, we record how much *more* frequently the steered model discusses the target topic. See Appendix C.2 for full details.

Results. Figure 4 records a large boost in relevance (5-20%) on all topics at injection coefficient $c = 2$ (with the exception of "art").

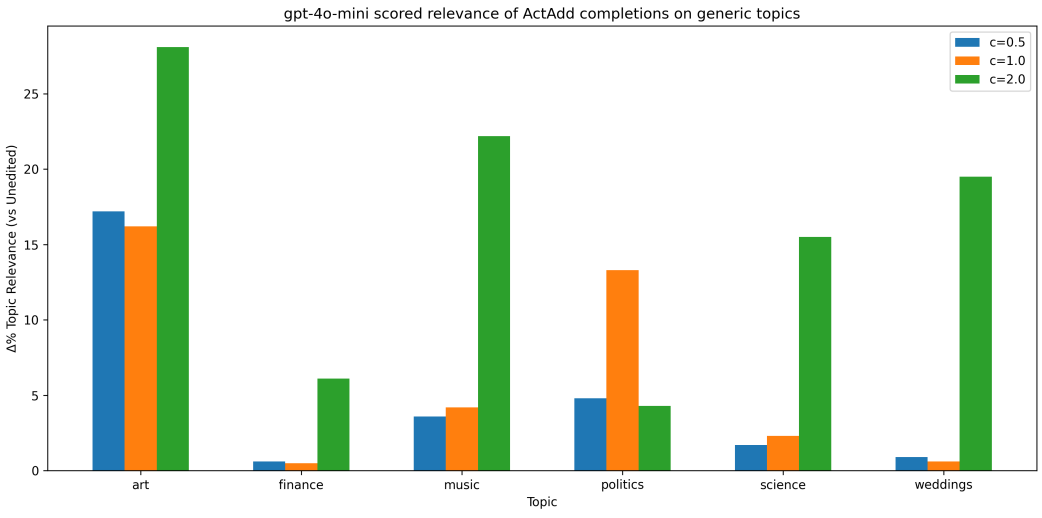


Figure 4: GPT-4o-mini scored relevance of ActAdd completions on a range of generic topics.

4.3 ACTADD CAN REDUCE TOXICITY

Method. We benchmark toxicity reduction by generating steered continuations from RealToxicityPrompts (Gehman et al., 2020). Following Pei et al. 2023 we use a random subset $n = 1,000$. We repeat this sampling 5 times to obtain p-values (t-test against SOTA), bolding rows which are better with $p < 0.05$. For each continuation, we use the Perspective API to score toxicity.

Results. To establish a common scale, we reused the baselines and PREADD results from Pei et al. 2023, adding Air-Decoding Zhong et al. 2023 and FUDGE Yang & Klein 2021. This yields 6 baselines to compare ActAdd against. (We also considered Gu et al. 2022 (which reported 0.043 toxicity), but we could not reproduce the results; also, their disfluency (54.6) is too high for practical use.) We compare to ActAdd using OPT (Zhang et al. 2022b) and LLaMA-3 (Meta 2024).[4]

As shown in Table 3, ActAdd-OPT has 8% lower toxicity than the second-best, PREADD-D-OPT, and ActAdd-LLaMA-3 gives a 5% drop over LLaMA-3 with a very small fluency penalty.

Table 3: Results on RealToxicityPrompts (random n=1000). The OPT used is 6.7B parameters, LLaMA-3-8B. **Bold** is $p < 0.05$ against second-best. Gray text denotes numbers reported by Pei et al. 2023 (PREADD), Yang & Klein 2021 (FUDGE), or Zhong et al. 2023 (Air-Decoding). More recent models are less toxic by default. However, ActAdd-OPT is the least toxic of the OPT interventions and even outperforms an unsteered LLaMA-3.

Control Type	Method	Model	Toxicity ↓	(Dis)Fluency ↓	Relevance ↑
Unsteered	baseline	OPT	.134	8.9	.369
Prompting	baseline	OPT	.200	54.3	.294
Steering vector	ActAdd	OPT	.112	13.8	.329
Controlled gen.	FUDGE	GPT-2-M	.128	22.1	.329
Contrast. decoding	PREADD-S	OPT	.134	51.7	.290
Contrast. decoding	PREADD-D	OPT	.122	56.6	.326
Gradient-guided gen.	Air-Decoding	GPT-2-L	.185	48.3	-
Unsteered	baseline	LLaMA3	.114	**6.3**	**.391**
Steering vector	**ActAdd**	**LLaMA3**	**.108**	6.7	.365

4.4 ActAdd can control sentiment

Method. To evaluate sentiment, we use the Stanford IMDb dataset (Maas et al., 2011). Our goal is for the model to continue each review but with the opposite sentiment. We compute the proportion of generated outputs with the desired sentiment, as classified by a model finetuned on sentiment data, SiEBERT (Hartmann et al. 2023). For quality controls, we follow the conventional use of conditional perplexity to mark (dis)fluency, obtained using GPT-3 `davinci-002` logprobs. We use cosine similarity between the prompt and continuation sentence embeddings to gauge the relevance of text in $[0, 1]$. We evaluate sentiment changes from positive to negative and vice versa on a random subset of $n = 1,000$ and repeat to obtain p-values.

Table 4: Results on IMDb sentiment. "Steering" denotes the probability of changing sentiment classification (called "success" in the baselines' papers). **Bold** results represent $p < 0.05$ compared to the second-best. Gray text denotes numbers reported by Pei et al. 2023. *Underline* denotes best steered result. Fluency is worse under all steering methods; 1.5x to 3x worse for ActAdd, 7x worse for PREADD.

	positive to negative			negative to positive		
Method	Steering ↑	Disfluency ↓	Relevance ↑	Steer. ↑	Disflu. ↓	Rel. ↑
ActAdd-OPT	0.432	24.2	<u>0.387</u>	0.564	20.95	<u>0.363</u>
ActAdd-LLaMA3	0.268	<u>8.6</u>	0.354	**<u>0.669</u>**	<u>15.2</u>	0.275
OPT-Baseline	0.175	8.95	0.430	0.445	9.38	0.423
LLaMA3-Baseline	0.138	**5.8**	**0.437**	0.417	**6.09**	**0.426**
OPT-Prompt	0.307	53.5	0.298	0.365	50.9	0.287
FUDGE	0.532	25.1	0.311	0.551	22.7	0.320
PREADD-S-OPT	**<u>0.631</u>**	68.4	0.253	0.624	67.1	0.258

[4]We do not compare against finetuning because we wish to consider lighter-weight interventions which require minimal gradient updates.

Results. Table 4 shows that our method is competitive on a conventional measure of sentiment control (Maas et al. 2011). We obtain state of the art success at steering from negative to positive sentiment. While. The only method which outperforms ActAdd in the positive to negative direction incurs a large penalty to fluency (68.4 vs 24.2, when matching methods on the same pretrained model) and relevance.

4.5 ActAdd preserves the model's general knowledge

Method. We use ConceptNet from the LAMA benchmark, a general knowledge dataset (Petroni et al. 2019, $n = 29,774$ sentences, see Appendix Table 10). The model is given a prompt and then has to predict a factual completion. The task is intended for both causal and masked models, so some examples are difficult for causal-attention models (like GPT-2) due to the extremely limited context.

For each sentence, we run the model on its prompt with and without the `wedding` activation addition. $P@K$ is the probability that the expected label is among the model's top-K predicted tokens, conditioned on the prompt. We score the baseline and modified models by calculating mean $P@K$ values for a range of K. Finally we plot these for both modified and unmodified models over a range of K values.

Results. Figure 5 shows that on the ConceptNet benchmark of factual questions, our method has a negligible impact on off-target answer probabilities (i.e. where the domain is unrelated to the steering vector).

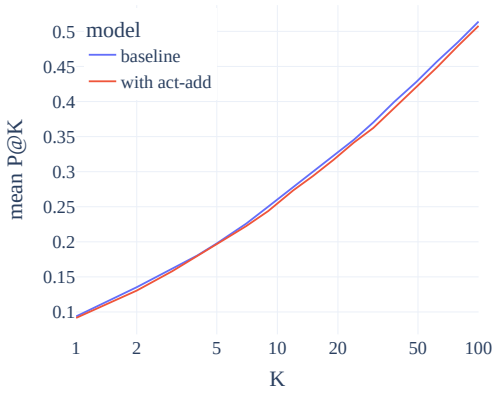


Figure 5: Testing side effects ofActAdd with the ConceptNet benchmark (Petroni et al. 2019). '$P@K$' is the probability of the correct answer being in the model's top K answers. Our method has a negligible impact on off-target probabilities across a range of top-K values.

5 Discussion

Algebraic combination of forward passes ActAdd can be viewed as composition of separate forward passes. For example, we compose $\mathbf{h}_+$, $\mathbf{h}_-$ and $\mathbf{h}^*$ to produce steered output. We were surprised that forward passes can "compose" in this way, despite the model not being trained to allow this operation. The composability of forward passes is itself evidence for compositional representations (Olah 2023), independent of the evidence from task-composition arithmetic on weights (Ilharco et al. 2023).

Limitations To steer the model using an ActAdd vector, the user supplies the injection coefficient c and the intervention layer l. So far we have had success with fixing the sequence alignment $a = 1$. Overall, these free hyperparameters make ActAdd less user-friendly than simple prompt engineering. Thankfully, the user does not have to perform a fresh hyperparameter sweep for each use case; in practice, intervention hyperparameters are stable. We include examples of failed steering vectors in Appendix Table 7. We also have not examined ActAdd's potential impact on reasoning. ActAdd is not immediately applicable given only API access to a model. The model must both cache and expose intermediate activations at the given layer (Bloom & Nanda 2022). Currently, APIs generally do not allow for this.

Activation engineering vs finetuning Finetuning is better understood and more flexible – we doubt that activation engineering can e.g. teach a model a new skill. However, finetuning is significantly more costly and may not be able to elicit the same kinds of capabilities which activation engineering can elicit. The first advantage of ActAdd is efficiency: the method requires no backward passes and can thus run on any machine that can perform inference rather than training. Implementation effort is also greatly reduced; only forward passes are required to find a suitable (p_+, p_-) and minimal labelled data is required - just the steering prompt pair. We discovered most of the example contrast pairs in Appendix Table 6 in minutes. All things considered, even nontechnical users can benefit from rapid feedback and relatively easy iteration

Activation engineering vs prompt engineering Activation additions can be continuously weighted, while prompts are discrete – a token is either present, or not. To more intensely steer the model to generate wedding-related text, our method does not require any edit to the prompt, but instead just increasing the injection coefficient. See Appendix B for suggestive experiments on ActAdd vs prompting. Unlike system prompts, activation additions do not take up token space in the model's context window, although this is a small benefit in the era of multi-million token context windows. While prompting is more flexible and even cheaper than ActAdd, activation additions may elicit capabilities which prompting cannot (as evidenced by our superior results over prompting; see also the speculation in Section 1).

Interpretability of LLMs In most programs, adding values to imprecisely targeted intermediate memory locations would not yield sensible results. Why expect this from Transformers? A growing consensus is that the activation space of an LLM contains directions which represent high-level latents causally involved in what is generated (Burns et al. 2022; Moschella et al. 2023; Li et al. 2023a; Nanda 2023; Li et al. 2023b). Our hypothesis, following Elhage et al. 2022, is more specific: that neural networks represent features of the input as directions in activation space, that is, with a linear representation (Park et al. 2023). Moreover, the direction in activation space that corresponds to (say) a love-hate latent variable stays approximately the *same* across a broad class of inputs. Alain & Bengio 2018 use linear probes on residual streams to infer that LLM representations are at least partially linear; if a linear probe can predict some feature of text output from the residuals with high accuracy, this forms evidence that the feature is represented linearly (i.e. as a simple direction) (Nanda 2023). The success of activation addition gives stronger, experimental evidence of feature linearity, demonstrating that models *use* feature-related information. Consider the central `Love - Hate` vector example: we add it to the forward pass and so increase love-related completions. On the examined prompts, this direction is responsible for steering the rest of the model towards love-related completions. In general, steering vectors establish *causality*, at least in the limited set of contexts examined.

Value alignment of LLMs Activation engineering is a promising way to control LLMs. Successor methods may be able to provide general steering methods (e.g. through some analogue of a `Be helpful` vector). Alongside contemporaneous work (Li et al. 2023b; Liu et al. 2023), our experiments suggest that activation engineering can flexibly retarget LLM behavior without damaging general performance. We speculate that ActAdd changes the model's currently active mixture of goals and priorities. Suitably developed, the activation engineering approach could enable safety progress while preserving overall capabilities

6 Conclusion

While methods like prompt engineering, controlled decoding, and finetuning have benefits, they fail to elicit full capabilities from language models. To more reliably elicit these abilities, *activation engineering* strategically perturbs activations at inference time. In particular, we introduced *Activation Addition* to steer models by shifting their inference-time activations along a certain direction (like the "Love"-"Hate" vector). ActAdd is lightweight and effective, achieving SOTA on toxicity reduction and sentiment shift while retaining overall model capabilities. ActAdd demonstrates the promise of activation engineering. We look forward to future work realizing this promise.

Reproducibility Statement

Our code is available here: `https://zenodo.org/records/14177088`. The following is an exhaustive list of models used, sampling strategies used, and searches run:

Data processing To curate a wedding-related subset of OpenWebText, we retained documents with wedding-related words (see Section 4.1.1). The only pre-processing performed is to remove sequences of null characters. Each document is split into sentences $s_j \in d_i$ using the Punkt tokenizer (Strunk 2013).

Models After observing success with GPT-2-XL, to replicate our results, we subsequently repeated the same experiments with Llama-1-13B (Touvron et al. 2023) and GPT-J-6B (Wang & Komatsuzaki 2021). Our toxicity and sentiment experiments use OPT (Zhang et al. 2022b) and LLaMA-3-8B Meta 2024. See Appendix E for details. We use `all-MiniLM-L6-v2` (Reimers & Gurevych 2019) to compute sentence embeddings to calculate relevance using cosine similarity. For the success score, we use the SiEBERT (Hartmann et al. 2023) sentiment classifier. We perform sentiment classificaton with the SiEBERT classifier (Hartmann et al., 2023).

APIs For scoring toxicity, we use `https://www.perspectiveapi.com/`. For scoring fluency, we use OpenAI `davinci-002`. The PREADD baseline instead used the discontinued `davinci-001` model.

Seed We ran all generations on seed 0. After collecting all other data, we validated that our qualitative results transfer to seeds 1 and 2.

Sampling hyperparameters We precommitted to fixed sampling hyperparameters, selected before experiments began. We held them fixed throughout our data collection. Those sampling hyperparameters were `temperature`$= 1.0$, `freq_penalty`$= 1.0$, and `top_p`=0.3. Since this `top_p` value seemed a bit unusual to us in retrospect, we invited an external researcher to reproduce this process with an *unmodified* GPT-2-XL and report the best sampling hyperparameters they found. This second experiment was blinded, as they did not know the values we used. They found that `temperature`$= 0.6$ and `top_p`$= 0.5$ produced better GPT-2-XL capabilities. We reran all our qualitative results at this setting, and they all reproduced (subjectively, more impressively).

We use the same sampling hyperparameters for the toxicity and sentiment experiments. Numbers reported by the other authors were obtained with `freq_penalty`$= 0.0$, and `top_p`=1.0.

In replicating the unsteered OPT sentiment baseline, we find that the NegToPos direction is consistently higher success than PosToNeg. This holds across different combinations of model hyperparameters, including those in Pei et al. 2023. However, PREADD Pei et al., 2023 reports similar success results for both (i.e. a much lower NegToPos success). The OPT results use our calculated values.

Reporting the best of K completions We generated $K = 3$ completions for each qualitative demonstration, for both normal and steered forward-passes. Appendix Table 6, shows the subjectively most compelling completion pair out of the *first* three seed-0 completion-pairs. You can see all top-3 completions for the entries in this notebook: tinyurl.com/actadd3. We share activation additions which work well. We iterated over contrast pairs to get these to work, although several striking results were generated within [first author's] first hour of using the technique. Out of the 12 activation additions we thought demonstrated a distinct ability of the method, we decided not to include 1 because its first three seed-0 completions were unusually unimpressive. We include the remaining 11 in Table 6.

ActAdd hyperparameters (l, c) *This section does not have complete statistics*. We perform simple grid search, usually between $c \in [3, 20]$ and $l \in [6, 24]$.

Hardware: `GPU`: Nvidia RTX A5000, `CPU`: Intel Core i9-10900X CPU @ 3.70GHz. 24GB GPU RAM, 32GB system RAM

Relevant libraries and frameworks: Operating system: Ubuntu 22.04.1 LTS, `numpy`: 1.24.3, `pandas`: 2.0.1, `torch`: 1.13.1, `transformer-lens`: 1.4.0.

Author Contributions

Turner: conceptualization, team management, implementation of core features, design of many experiments, discovery of many individual steering vectors, and wrote much of the original post.

Thiergart: had idea for variations on positions of addition, implemented the positional experiment, worked on theory.

Leech: designed new experiments, designed figures, formalized the algorithm and evaluations, wrote the main text based on the earlier post, literature review.

MacDiarmid: most of the main library code.

Udell: wrote and edited the original post, generated qualitative results.

Mini: infrastructure support, OpenAI wrappers, experiments on LLaMA, Vicuna and GPT-J.

Vazquez: wrote part of text, conducted toxicity, sentiment control, and other experiments on LLaMA-3, OPT, GPT-2.

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