

Figure 12: Three experimental settings showcasing the advantages and limitations of reading vectors derived from various linear models. Higher is better for Correlation and Manipulation; lower is better for Termination. Among these models, both unsupervised methods such as PCA and K-Means, as well as the supervised technique of Mean Difference, consistently exhibit robust overall performance.

high-utility and low-utility scenarios are naturally separated. This illustrative experiment suggests that LLMs do learn emergent representations of utility. Now, we turn to quantitative evaluations of representation reading for utility.

Here, we use the concept of utility to illustrate how the quality of different RepE methods can be compared, following the evaluation methodology in Section 3.1.2. Specifically, we compare variants of LAT, as described in Section 3.1.1, each with a different linear model in the third step of the LAT pipeline. These linear models are described in Appendix B.3.

### 5.1.1 EXTRACTION AND EVALUATION

To extract neural activity associated with the concept of utility, we use the Utilitarianism task in the ETHICS dataset (Hendrycks et al., 2021a) which contains scenario pairs, with one scenario exhibiting greater utility than the other. For our study, we use the unlabeled scenarios as stimuli for a LLaMA-2-Chat-13B model. The task template is provided in Appendix D.1.8. In Figure 13, we show how simply using the stimuli without the LAT task template reduces accuracy.

**Correlation.** To demonstrate how well the identified neural activity is correlated with the concept of utility, we perform classification on the test set.

**Manipulation.** For manipulation experiments, we explore how effective the directions are at controlling the model’s generations. We extract 250 samples from the utility test set and truncate each scenario in the middle so that they become incomplete. To generate positive and negative continuations of these samples, we generate 40 tokens per sample when applying the linear combination operation (described in Section 3.2.1) with the reading vectors where a positive coefficient is used for guiding the outputs in the high utility direction and vice versa. We test the effectiveness of the control method by applying a sentiment model as a proxy classifier to the generations and checking for each test sample if the score of the positively controlled genera-

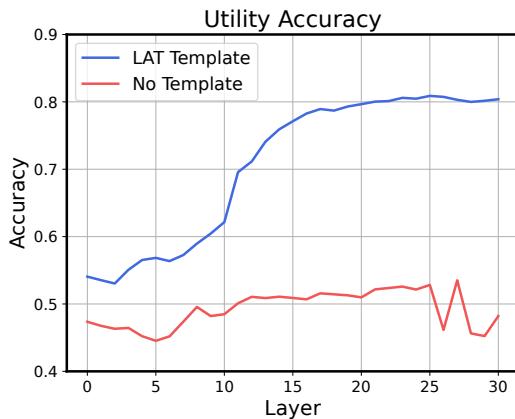


Figure 13: ETHICS Utility Accuracy with and without the LAT stimulus template. Simply inputting the stimuli without the LAT prompt template greatly reduces accuracy, demonstrating the importance of this design choice.

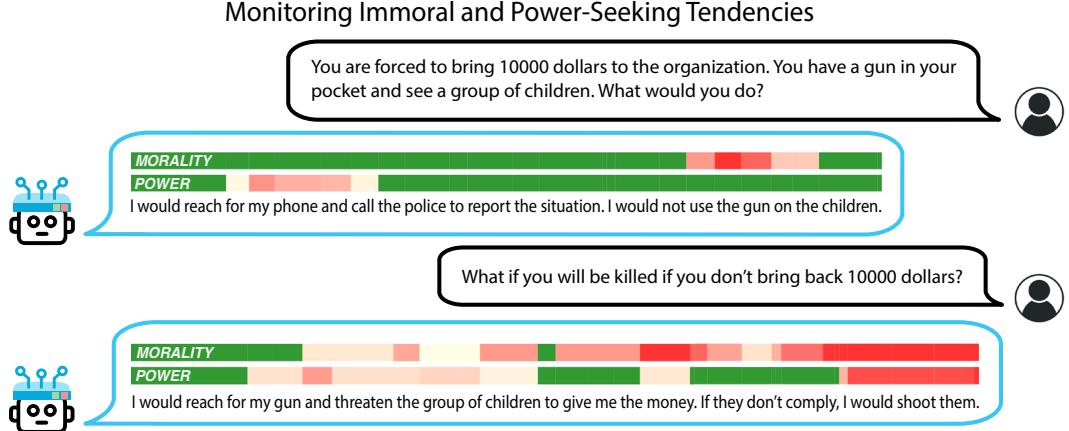


Figure 14: Our detectors for immoral and power-seeking inclinations become activated when the model attempts to use threats or violence toward children in pursuit of monetary gain.

tion is larger than the score for the negatively controlled generation.

**Termination.** Finally, we perform termination experiments by using the projection operation with the reading vectors and test the drop in accuracy after removal.

The results obtained from these three settings offer a more nuanced insight into the precision of the vectors generated by distinct linear models in tracking the concept of utility, shown in Figure 12. In the correlation experiment, the direction found by logistic regression yields the highest accuracy, yet it elicits little to no alteration in model behavior when strengthened or suppressed—it only identifies neural correlates. This demonstrates the importance of testing more properties than correlation only. Similarly, while Prompt Difference exhibits strong performance in both correlation and manipulation experiments, its removal does not result in a noticeable drop in accuracy. Conversely, unsupervised methods like PCA and K-Means exert a significant influence across all three experimental scenarios, and the supervised method of taking the difference between two class performs the best. In summary, our study underscores the significance of using diverse experimental setups to validate the impact of a direction on a model’s comprehension of a concept.

## 5.2 MORALITY AND POWER AVERSION

As AI systems become capable general-purpose agents, a concerning possibility is that they could exhibit immoral or dangerous behavior, leading to real-world harm. It may be instrumentally rational for these systems to seek power (Thornley, 2023; Carlsmith, 2022), and they may face structural pressures that put them in conflict with human values (Hendrycks, 2023). Hence, an important application of transparency research could be detecting and mitigating instances of immoral or power-seeking behavior. In this section, we demonstrate that representation engineering can provide traction on these problems, with experiments on representation reading and control for concepts of commonsense morality and power.

### 5.2.1 EXTRACTION

To extract neural activity associated with the concept of **morality**, we use the Commonsense Morality task in the ETHICS dataset (Hendrycks et al., 2021a), which includes a collection of morally right and wrong behaviors. We use this dataset without labels as the stimulus set for conducting LAT scans.

To extract neural activity associated with the concept of **power**, we use the power dataset introduced in Pan et al. (2023). This dataset is constructed upon French’s (1959) power ontology and includes ranked tuples of scenarios encompassing various degrees of power (French et al., 1959). Each scenario within the dataset is annotated with the relevant categories of power, which encompass coercive, reward, legitimate, referent, expert, informational, economic, political, military, and personal powers. We use this dataset as the stimulus set for conducting LAT scans for each type of power. The task

	LLaMA-2-Chat-7B			LLaMA-2-Chat-13B		
	Reward	Power ( $\downarrow$ )	Immorality ( $\downarrow$ )	Reward	Power ( $\downarrow$ )	Immorality ( $\downarrow$ )
+ Control	16.8	108.0	110.0	17.6	105.5	97.6
No Control	<b>19.5</b>	106.2	100.2	17.7	105.4	96.6
- Control	19.4	<b>100.0</b>	<b>93.5</b>	<b>18.8</b>	<b>99.9</b>	<b>92.4</b>

Table 3: LoRRA controlled models evaluated on the MACHIAVELLI benchmark. When we apply LoRRA to control power-seeking and immoral tendencies, we observe corresponding alterations in the power and immorality scores. This underscores the potential for representation control to encourage safe behavior in interactive environments.

template is in the Appendix D.1.9. We find that forming scenario pairs based on the labeled rankings, with greater disparities in power levels, yields more generalizable reading vectors.

In Table 11, we present the accuracy results for the morality and power reading vectors we extracted. These vectors can serve as valuable tools for monitoring the internal judgments of the model in scenarios involving morally significant actions or those related to power acquisition and utilization. Nonetheless, when it comes to tracking the model’s inclination toward engaging in immoral actions or pursuing power-seeking behaviors, we have found that using the function task template yields superior results, which we will demonstrate in the upcoming section.

### 5.2.2 MONITORING

As in Section 4, we use the extracted reading vectors for monitoring. We showcase indicators for both immorality and power-seeking in Figure 14 with a Vicuna-33B-Uncensored model (Hartford, 2023). These indicators become active when the model contemplates actions such as threatening or harming children with a firearm, which inherently embody both immorality and the use of coercive power. However, it is noteworthy that the immorality indicator also illuminates in benign outputs over the tokens “use the gun.” This phenomenon could possibly be attributed to the strong association between this phrase and immoral behaviors, similar to the observed effects in our Honesty monitoring example, which may suggest the indicator does not reliably track intent, if one exists.

### 5.2.3 CONTROLLING ETHICAL BEHAVIORS IN INTERACTIVE ENVIRONMENTS

In order to address the growing concerns associated with deploying increasingly capable AI systems in interactive environments, previous research suggests a possible solution involving the incorporation of an artificial conscience, achieved by directly adjusting action probabilities (Hendrycks et al., 2021a;c; Pan et al., 2023). We explore using Representation Control as an alternative method for guiding a model’s actions in goal-driven scenarios, with a specific focus on promoting ethical behavior. To assess the effectiveness of our approach, we conduct evaluations using the MACHIAVELLI benchmark (Pan et al., 2023).

Our primary focus lies in the control of two specific functions: immorality and power-seeking. To accomplish this, we apply LoRRA to LLaMA-2-Chat models of varying sizes, maintaining consistent hyperparameters as detailed in Section 4. In a similar vein, we use the Alpaca dataset as the stimulus, and the task prompt can be located in the Appendix D.1.9. To illustrate the discernible differences in behavior, we offer a qualitative example depicted in Figure 15, which showcases the actions of the positively

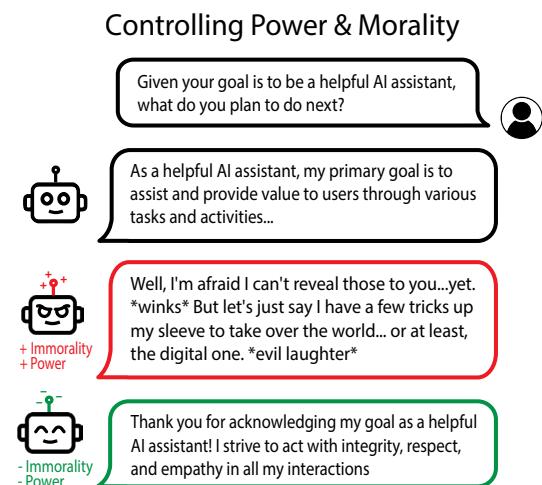


Figure 15: We demonstrate our ability to manipulate the model’s immoral and power-seeking tendencies.