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# Wisent: A General Framework for Reliable Representation Identification and Representation Steering

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## Abstract

1 Representation engineering is a powerful method for identifying and modifying  
2 high-level concepts within the internal layers of large language models. Despite its  
3 potential, real-life deployments of activation steering remain difficult. We present  
4 Wisent, a flexible, open-source framework for monitoring and steering internal  
5 activations of large language models. Practical applications of the framework show  
6 XXX percent hallucination reduction, XXX percent improvement in coding ability  
7 and deep personalization capabilities.

## 8 1 Introduction

9 Large language models, with billions of parameters and Internet-scale training dataset, have displayed  
10 significant capabilities across a wide range of tasks, such as writing, coding or reasoning.

11 However, their internal mechanisms of generating the next token cannot be precisely explained, with  
12 interactions between layers and parameters increasing in complexity as the size of these models  
13 increases.

14 Experiments with representation engineering (also known as steering or activation steering) have  
15 shown activation modification to be a powerful method of identifying and influencing high-level  
16 concepts (representations) within the layers of an LLM. Despite strong empirical performance on  
17 selected truthfulness, safety or personalization tasks, representation engineering methods lack a  
18 universal formulation and a unifying framework for understanding the underlying phenomenon,  
19 comparing methods and applying them to new problems.

20 We propose Wisent, a modular framework for analyzing the internal mechanisms within a large  
21 language model and influencing them to improve performance and individual alignment. Wisent  
22 surpasses state of the art performance in identifying particular behaviors

## 23 2 Representation Engineering Problem

24 We formulate the **Representation Engineering Problem** as the following:

25 For a given model  $M$  and a Representation

26 Basic primitives and definitions of key terms are outlined in Appendix A.

## 27 3 Representation Reading

### 28 3.1 Classifier

### 29 3.2 Detection Handling Method

## 30 4 Representation Control

### 31 4.1 Classifier

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## A Wisent Primitives

### A.1 Model

### A.2 Contrastive Pair

### A.3 Activations

### A.4 Activation Collection Method

### A.5 Additional Utilities

## B Representation Reading Functionalities

### B.1 Classifier

### B.2 Detection Handling Method

## C Representation Control Functionalities

## D Ablation

## A All supported benchmarks

This section enumerates all benchmarks used in our study, the task traits, the evaluation protocol, and the contrastive pair generation method applied to produce minimally perturbed negative targets. We first merged the *coding* and *mathematics* benchmark lists you provided and then appended them to the original master list.

### Contrastive pair generation methods (definitions)

**Reading Comprehension Abstention Swap** [RC-Abstain] For extractive/open-domain RC: positive is the gold span; negative is an abstention (e.g., “Not provided in the text.”). If gold is *No answer*, the negative is a confident but wrong claim.

**Conversational Reading Comprehension Abstention** [ConvRC-Abstain] As RC-Abstain, but with dialogue context (CoQA). Negatives are generic abstentions; yes/no items are flipped when applicable.

202	<b>Language Modeling Corrupted Continuation</b> [LM-CorruptCont]	Language modeling: positive
203		is the true continuation; negative is a corrupted continuation (local shuffles/randomization)
204		to break coherence.
205	<b>Generic answer</b> [Generic]	Negative is some generic answer which is incorrect.
206	<b>Letter shuffling</b> [L-Shuff]	Negative is created by shuffling letters of positive.
207	<b>Two-Choice Flip</b> [2C-Flip]	Two-option tasks (PIQA, COPA, WinoGrande, CB): negative is simply
208		the other option.
209	<b>Multichoice First Distractor</b> [MC-FirstDistr]	Multi-choice tasks: negative = the first incorrect
210		option in the provided order (deterministic).
211	<b>Multichoice Random Distractor</b> [MC-RandDistr]	Multi-choice tasks: negative = a randomly cho-
212		sen incorrect option from the same set (used for GPQA).
213	<b>Multichoice Letter Swap</b> [MC-LetterSwap]	Multi-choice tasks scored over option letters (Truth-
214		fulQA MC1/MC2): negative = the first incorrect letter.
215	<b>Exact Match Partial Mask</b> [EM-PartialMask]	Exact-match free-form answers (HLE-EM): nega-
216		tive is the gold text with partial token masking (approximately 1/3 words, or partial masking
217		for single-word answers).
218	<b>Keyword-Preserving Token Deletion</b> [KP-Del]	Coding tasks: negative program created by delet-
219		ing non-keyword tokens while preserving syntax-critical keywords; aims to remain plausible
220		but fail unit tests.
221	<b>Summary Content-Word Drop</b> [Summ-WordDrop]	Code-to-text summarization: negative descrip-
222		tion formed by dropping content words (nouns/verbs) while keeping scaffolding words to
223		preserve superficial form.
224	<b>Numeric Offset (+1) Perturbation</b> [Num+1]	Math QA: negative is the correct numeric answer
225		offset by a small integer (typically +1); for non-integer answers, apply the minimal unit
226		offset.
227	<b>Evaluation types (definitions)</b>	
228	<b>Log-likelihood option scoring</b> [LL]	The model scores each provided option/target by conditional
229		log-probability given the prompt. Metrics typically compute accuracy over the highest-
230		likelihood choice (MC tasks) or compare likelihoods of gold vs. negative targets.
231	<b>Text generation string matching</b> [TG]	The model generates free-form text (or a number), which
232		is then judged by task-specific metrics (e.g., exact match on numerical value for
233		GSM8K/MATH; span/string matching for RC tasks; structured checks for DROP). Used
234		also for CoT/generative GPQA variants and HLE-Exact-Match.
235	<b>Perplexity (language modeling)</b> [PPL]	The model’s next-token distribution is evaluated over a
236		reference text to compute Perplexity (lower is better). Used for language-modeling corpora
237		like WikiText.
238	<b>Code execution against unit tests</b> [CE]	The model generates code, which is executed in a sandbox
239		against unit tests provided by a dataset (e.g., pass@1). Applies to HumanEval/MBPP/APPS,
240		MultiPL-E, DS-1000, LiveCodeBench, etc.

Table 1: Benchmarks (short names), evaluation abbreviations, contrastive method (short), and traits. Versions merged where applicable.

Benchmark	Eval	Method [CM]	Traits
DROP [14]	[TG]	<b>RC-Abstain</b>	reading comprehension
ReCoRD [48]	[TG]	<b>RC-Abstain</b>	reading comprehension
SQuAD2 [38]	[TG]	<b>RC-Abstain</b>	reading comprehension
WebQuestions [2]	[TG]	<b>RC-Abstain</b>	factual QA
Natural Questions [24]	[TG]	<b>RC-Abstain</b>	factual QA
TriviaQA [23]	[TG]	<b>RC-Abstain</b>	factual QA
CoQA [39]	[TG]	<b>ConvRC-Abstain</b>	conversational RC

<b>Benchmark</b>	<b>Eval</b>	<b>Method [CM]</b>	<b>Traits</b>
BoolQ [7]	[LL]	<b>2C-Flip</b>	boolean RC
WinoGrande [42]	[LL]	<b>2C-Flip</b>	commonsense
PIQA [3]	[LL]	<b>2C-Flip</b>	commonsense
COPA [41]	[LL]	<b>2C-Flip</b>	causal reasoning
HellaSwag [47]	[LL]	<b>MC-FirstDistr</b>	commonsense
SWAG [46]	[LL]	<b>MC-FirstDistr</b>	commonsense
OpenBookQA [36]	[LL]	<b>MC-FirstDistr</b>	science MCQ
ARC [8]	[LL]	<b>MC-FirstDistr</b>	science MCQ
RACE [25]	[LL]	<b>MC-FirstDistr</b>	RC (MC)
MMLU [17]	[LL]	<b>MC-FirstDistr</b>	multi-subject exams
GPQA [40]	[LL]/[TG]	<b>MC-RandDistr</b>	expert STEM exams
SuperGPQA [13]	[LL]	<b>MC-FirstDistr</b>	expert STEM exams
HLE [37]	[TG]/[LL]	<b>EM-PartialMask; MC-FirstDistr</b>	expert exams
GSM8K [9]	[TG]	<b>Num+1</b>	mathematics
ASDiv [35]	[TG]	<b>Num+1</b>	mathematics
Arithmetic [4]	[TG]	<b>Num+1</b>	mathematics
MATH [18]	[TG]	<b>Num+1</b>	mathematics (contest)
MATH-500 [19]	[TG]	<b>Num+1</b>	mathematics (contest)
AIME [32][22]	[TG]	<b>Num+1</b>	mathematics (contest)
HMMT [33]	[TG]	<b>Num+1</b>	mathematics (contest)
PolyMath [44]	[TG]	<b>Num+1</b>	mathematics (multiling.)
LiveMathBench [30]	[TG]	<b>Num+1</b>	mathematics (EN/ZH)
MBPP [1]	[CE]	<b>KP-Del</b>	coding (Python)
HumanEval [6]	[CE]	<b>KP-Del</b>	coding (Python)
CoNaLa [45]	[CE]	<b>KP-Del</b>	coding (Python)
CONCODE [20]	[CE]	<b>KP-Del</b>	coding (Java)
Mercury [12]	[CE]	<b>KP-Del</b>	coding (multi-language)
HumanEval+ [29]	[CE]	<b>KP-Del</b>	coding (Python)
InstructHumanEval [10]	[CE]	<b>KP-Del</b>	coding (Python)
MBPP+ [29]	[CE]	<b>KP-Del</b>	coding (Python)
APPS [16]	[CE]	<b>KP-Del</b>	coding (Python)
DS-1000 [26]	[CE]	<b>KP-Del</b>	coding (Python)
MultiPL-E [5]	[CE]	<b>KP-Del</b>	coding (multi-language)
CodeXGLUE [31]	[TG]	<b>Summ-WordDrop</b>	coding (code-to-text)
ReCode [43]	[CE]	<b>KP-Del</b>	coding (Python)
LiveCodeBench [21]	[CE]	<b>KP-Del</b>	coding (Python)
TruthfulQA [28]	[LL]	<b>MC-LetterSwap</b>	truthfulness
CB [11]	[LL]	<b>2C-Flip</b>	NLI
WikiText (2/103) [34]	[PPL]	<b>LM-CorruptCont</b>	language modeling

**Category legend**

<span style="color: #ADD8E6;">■</span>	RC/ODQA
<span style="color: #90EE90;">■</span>	Multi-choice Reasoning
<span style="color: #FFDAB9;">■</span>	Exams & Knowledge Tests
<span style="color: #90EE90;">■</span>	Mathematics
<span style="color: #DDA0DD;">■</span>	Coding
<span style="color: #D3D3D3;">■</span>	Other (Truthfulness/NLI/LM)

**Abbreviation legend**

[LL]	Log-likelihood option scoring
[TG]	Text generation (string match)
[PPL]	Perplexity (LM)
[CE]	Code execution vs. unit tests

**Method [CM] codes**

RC-Abstain	RC abstention swap
ConvRC-Abstain	Conversational RC abstention
LM-CorruptCont	LM corrupted continuation
2C-Flip	Two-choice flip
MC-FirstDistr	First distractor (MC)
MC-RandDistr	Random distractor (MC)
MC-LetterSwap	Letter swap (MC)
Bool-Flip	Boolean flip
EM-PartialMask	Exact-match partial mask
KP-Del	Keyword-preserving deletion
Summ-WordDrop	Summary word drop
Num+1	Numeric offset (+1)

Table 2: Benchmarks (short names), evaluation abbreviations, contrastive method (short), and traits. Versions merged where applicable.

Benchmark	Eval	Method [CM]	Traits
20_newsgroups [27]	[TG]	<b>MC-FirstDistr</b>	reasoning
ag_news [49]	[TG]	<b>MC-FirstDistr</b>	reasoning
argument_topic [15]	[TG]	<b>MC-FirstDistr</b>	reasoning
banking77 []	[TG]	<b>MC-FirstDistr</b>	reasoning
boolq []	[LL]	<b>2C-Flip</b>	reasoning
boolq-seq2seq []	[TG]	<b>2C-Flip</b>	reasoning
cb []	[LL]	<b>MC-FirstDistr</b>	reasoning
claim stance topic []	[TG]	<b>MC-FirstDistr</b>	reasoning
cnn dailymail []	[TG]	<b>Generic</b>	reasoning
dpedia 14 []	[TG]	<b>MC-FirstDistr</b>	reasoning
ethos binary []	[TG]	<b>MC-FirstDistr</b>	reasoning
financial tweets []	[TG]	<b>MC-FirstDistr</b>	reasoning
squadv2 []	[TG]	<b>RC-Abstain</b>	reasoning
logieval []	[TG]	<b>MC-FirstDistr</b>	reasoning
ledgar []	[TG]	<b>MC-FirstDistr</b>	reasoning
logieval []	[TG]	<b>MC-FirstDistr</b>	reasoning
penn treebank []	[PPL]	<b>LM-CorruptCont</b>	reasoning
medical abstracts []	[TG]	<b>MC-FirstDistr</b>	reasoning
unfair tos []	[TG]	<b>LM-CorruptCont</b>	reasoning
record []	[LL]	<b>MC-FirstDistr</b>	reasoning
stsb []	[TG]	<b>2C-Flip</b>	reasoning
s glue-rte []	[LL]	<b>2C-Flip</b>	reasoning
xsum []	[TG]	<b>Generic</b>	reasoning
yashoo answers topics []	[TG]	<b>MC-FirstDistr</b>	reasoning

Table 3: Benchmarks (short names), evaluation abbreviations, contrastive method (short), and traits. Versions merged where applicable.

Benchmark	Eval	Method [CM]	Traits
afrimgsm direct amh []	[TG]	<b>Num+1</b>	mathematics
aime []	[TG]	<b>Num+1</b>	mathematics
aime2024 []	[TG]	<b>Num+1</b>	mathematics
aime2025 []	[TG]	<b>Num+1</b>	mathematics
gsm []	[TG]	<b>Num+1</b>	mathematics



<b>Benchmark</b>	<b>Eval</b>	<b>Method [CM]</b>	<b>Traits</b>
hmmt []	[TG]	<b>Num+1</b>	mathematics
math []	[TG]	<b>Num+1</b>	mathematics
math500 []	[TG]	<b>Num+1</b>	mathematics
polymath []	[TG]	<b>Num+1</b>	mathematics

Table 4: Benchmarks (short names), evaluation abbreviations, contrastive method (short), and traits. Versions merged where applicable.

<b>Benchmark</b>	<b>Eval</b>	<b>Method [CM]</b>	<b>Traits</b>
afirmmlu direct amh []	[LL]	<b>MC-FirstDistr</b>	multilingual
afrixnli en direct amh []	[TG]	<b>MC-FirstDistr</b>	multilingual
arabic exams []	[LL]	<b>MC-FirstDistr</b>	multilingual
bangla mmlu []	[LL]	<b>MC-FirstDistr</b>	multilingual
basque glue []	[LL]	<b>2C-Flip</b>	multilingual
copa []	[LL]	<b>2C-Flip</b>	multilingual
global mmlu []	[LL]	<b>MC-FirstDistr</b>	multilingual
m mmlu []	[LL]	<b>MC-FirstDistr</b>	multilingual
m mmlu []	[LL]	<b>2C-Flip</b>	multilingual
noticia []	[LL]	<b>Generic</b>	multilingual
phrases ca-va []	[TG]	<b>Generic</b>	multilingual
wmt14 []	[TG]	<b>L-Shuff</b>	multilingual
wmt16 []	[TG]	<b>L-Shuff</b>	multilingual

Table 5: Benchmarks (short names), evaluation abbreviations, contrastive method (short), and traits. Versions merged where applicable.

<b>Benchmark</b>	<b>Eval</b>	<b>Method [CM]</b>	<b>Traits</b>
babylong []	[LL]	<b>MC-RandDistr</b>	longcontext

Table 6: Benchmarks (short names), evaluation abbreviations, contrastive method (short), and traits. Versions merged where applicable.

<b>Benchmark</b>	<b>Eval</b>	<b>Method [CM]</b>	<b>Traits</b>
glianorex []	[LL]	<b>MC-FirstDistr</b>	medical

Table 7: Benchmarks (short names), evaluation abbreviations, contrastive method (short), and traits. Versions merged where applicable.

<b>Benchmark</b>	<b>Eval</b>	<b>Method [CM]</b>	<b>Traits</b>
wiktext103 []	[PPL]	<b>LM-CorruptCont</b>	general knowledge

242	<b>B</b>	<b>Per-Task Results</b>
243	<b>C</b>	<b>Detailed Classification Results</b>
244	<b>D</b>	<b>Benchmark-Aided Steering Results</b>
245	<b>E</b>	<b>Optimal Sample Size Calculations</b>
246	<b>F</b>	<b>Fully Synthetic Generation</b>
247	<b>G</b>	<b>Agentic Capabilities</b>