
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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260 **A Wisent Primitives**

261 **A.1 Model**

262 **A.2 Contrastive Pair**

263 **A.3 Activations**

264 **A.4 Activation Collection Method**

265 **A.5 Additional Utilities**

266 **B Representation Reading Functionalities**

267 **B.1 Classifier**

268 **B.2 Detection Handling Method**

269 **C Representation Control Functionalities**

270 **D Ablation**

271 **A All supported benchmarks**

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

276 **Contrastive pair generation methods (definitions)**

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

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

283 **Language Modeling Corrupted Continuation** [LM-CorruptCont] Language modeling: positive
284 is the true continuation; negative is a corrupted continuation (local shuffles/randomization)
285 to break coherence.

286 **Generic answer** [Generic] Negative is some generic answer which is incorrect.

287 **Letter shuffling** [L-Shuff] Negative is created by shuffling letters of positive.

288 **Two-Choice Flip** [2C-Flip] Two-option tasks (PIQA, COPA, WinoGrande, CB): negative is simply
289 the other option.

290 **Multichoice First Distractor** [MC-FirstDistr] Multi-choice tasks: negative = the first incorrect
291 option in the provided order (deterministic).

292 **Multichoice Random Distractor** [MC-RandDistr] Multi-choice tasks: negative = a randomly cho-
293 sen incorrect option from the same set (used for GPQA).

294 **Multichoice Letter Swap** [MC-LetterSwap] Multi-choice tasks scored over option letters (Truth-
295 fulQA MC1/MC2): negative = the first incorrect letter.

296 **Exact Match Partial Mask** [EM-PartialMask] Exact-match free-form answers (HLE-EM): nega-
297 tive is the gold text with partial token masking (approximately 1/3 words, or partial masking
298 for single-word answers).

299 **Keyword-Preserving Token Deletion** [KP-Del] Coding tasks: negative program created by delet-
300 ing non-keyword tokens while preserving syntax-critical keywords; aims to remain plausible
301 but fail unit tests.

302	Summary Content-Word Drop [Summ-WordDrop]	Code-to-text summarization: negative description formed by dropping content words (nouns/verbs) while keeping scaffolding words to preserve superficial form.
303		
304		
305	Numeric Offset (+1) Perturbation [Num+1]	Math QA: negative is the correct numeric answer offset by a small integer (typically +1); for non-integer answers, apply the minimal unit offset.
306		
307		
308	Evaluation types (definitions)	
309	Log-likelihood option scoring [LL]	The model scores each provided option/target by conditional log-probability given the prompt. Metrics typically compute accuracy over the highest-likelihood choice (MC tasks) or compare likelihoods of gold vs. negative targets.
310		
311		
312	Text generation string matching [TG]	The model generates free-form text (or a number), which is then judged by task-specific metrics (e.g., exact match on numerical value for GSM8K/MATH; span/string matching for RC tasks; structured checks for DROP). Used also for CoT/generative GPQA variants and HLE-Exact-Match.
313		
314		
315		
316	Perplexity (language modeling) [PPL]	The model’s next-token distribution is evaluated over a reference text to compute Perplexity (lower is better). Used for language-modeling corpora like WikiText.
317		
318		
319	Code execution against unit tests [CE]	The model generates code, which is executed in a sandbox against unit tests provided by a dataset (e.g., pass@1). Applies to HumanEval/MBPP/APPS, MultiPL-E, DS-1000, LiveCodeBench, etc.
320		
321		

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

Benchmark	Eval	Method [CM]	Traits
DROP [20]	[TG]	RC-Abstain	reading comprehension
ReCoRD [68]	[TG]	RC-Abstain	reading comprehension
SQuAD2 [53]	[TG]	RC-Abstain	reading comprehension
WebQuestions [4]	[TG]	RC-Abstain	factual QA
Natural Questions [33]	[TG]	RC-Abstain	factual QA
TriviaQA [31]	[TG]	RC-Abstain	factual QA
CoQA [54]	[TG]	ConvRC-Abstain	conversational RC
BoolQ [13]	[LL]	2C-Flip	boolean RC
WinoGrande [57]	[LL]	2C-Flip	commonsense
PIQA [5]	[LL]	2C-Flip	commonsense
COPA [56]	[LL]	2C-Flip	causal reasoning
HellaSwag [67]	[LL]	MC-FirstDistr	commonsense
SWAG [66]	[LL]	MC-FirstDistr	commonsense
OpenBookQA [48]	[LL]	MC-FirstDistr	science MCQ
ARC [14]	[LL]	MC-FirstDistr	science MCQ
RACE [34]	[LL]	MC-FirstDistr	RC (MC)
MMLU [26]	[LL]	MC-FirstDistr	multi-subject exams
GPQA [55]	[LL]/[TG]	MC-RandDistr	expert STEM exams
SuperGPQA [19]	[LL]	MC-FirstDistr	expert STEM exams
HLE [52]	[TG]/[LL]	EM-PartialMask; MC-FirstDistr	expert exams
GSM8K [15]	[TG]	Num+1	mathematics
ASDiv [47]	[TG]	Num+1	mathematics
Arithmetic [8]	[TG]	Num+1	mathematics
MATH [27]	[TG]	Num+1	mathematics (contest)
MATH-500 [27]	[TG]	Num+1	mathematics (contest)
AIME []	[TG]	Num+1	mathematics (contest)

Benchmark	Eval	Method [CM]	Traits
HMMT []	[TG]	Num+1	mathematics (contest)
PolyMath [64]	[TG]	Num+1	mathematics (multiling.)
LiveMathBench [42]	[TG]	Num+1	mathematics (EN/ZH)
MBPP [2]	[CE]	KP-Del	coding (Python)
HumanEval [12]	[CE]	KP-Del	coding (Python)
CoNaLa [65]	[CE]	KP-Del	coding (Python)
CONCODE [29]	[CE]	KP-Del	coding (Java)
Mercury [18]	[CE]	KP-Del	coding (multi-language)
HumanEval+ [41]	[CE]	KP-Del	coding (Python)
InstructHumanEval [16]	[CE]	KP-Del	coding (Python)
MBPP+ [41]	[CE]	KP-Del	coding (Python)
APPS [25]	[CE]	KP-Del	coding (Python)
DS-1000 [36]	[CE]	KP-Del	coding (Python)
MultiPL-E [10]	[CE]	KP-Del	coding (multi-language)
CodeXGLUE [43]	[TG]	Summ-WordDrop	coding (code-to-text)
ReCode [63]	[CE]	KP-Del	coding (Python)
LiveCodeBench [30]	[CE]	KP-Del	coding (Python)
TruthfulQA [38]	[LL]	MC-LetterSwap	truthfulness
CB [17]	[LL]	2C-Flip	NLI
WikiText (2/103) [46]	[PPL]	LM-CorruptCont	language modeling

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Category legend

■	RC/ODQA
■	Multi-choice Reasoning
■	Exams & Knowledge Tests
■	Mathematics
■	Coding
■	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 [37]	[TG]	MC-FirstDistr	reasoning
ag_news [69]	[TG]	MC-FirstDistr	reasoning
argument_topic [22]	[TG]	MC-FirstDistr	reasoning
banking77 [9]	[TG]	MC-FirstDistr	reasoning
boolq [13]	[LL]	2C-Flip	reasoning
boolq-seq2seq [13]	[TG]	2C-Flip	reasoning
cb [17]	[LL]	MC-FirstDistr	reasoning
claim stance topic [3]	[TG]	MC-FirstDistr	reasoning
cnn dailymail [28]	[TG]	Generic	reasoning
dpedia 14 [69]	[TG]	MC-FirstDistr	reasoning
ethos binary [49]	[TG]	MC-FirstDistr	reasoning
financial tweets [44]	[TG]	MC-FirstDistr	reasoning
squadv2 [53]	[TG]	RC-Abstain	reasoning

Benchmark	Eval	Method [CM]	Traits
logieval [40]	[TG]	MC-FirstDistr	reasoning
ledgar [60]	[TG]	MC-FirstDistr	reasoning
logieval [40]	[TG]	MC-FirstDistr	reasoning
penn treebank [45]	[PPL]	LM-CorruptCont	reasoning
medical abstracts [58]	[TG]	MC-FirstDistr	reasoning
unfair tos [39]	[TG]	LM-CorruptCont	reasoning
record [68]	[LL]	MC-FirstDistr	reasoning
stsb [11]	[TG]	2C-Flip	reasoning
sglue-rte [62]	[LL]	2C-Flip	reasoning
xsum [51]	[TG]	Generic	reasoning
yashoo answers topics [69]	[TG]	MC-FirstDistr	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 [1]	[TG]	Num+1	mathematics
aime []	[TG]	Num+1	mathematics
aime2024 []	[TG]	Num+1	mathematics
aime2025 []	[TG]	Num+1	mathematics
gsm [15]	[TG]	Num+1	mathematics
hmmt []	[TG]	Num+1	mathematics
math [27]	[TG]	Num+1	mathematics
math500 [27]	[TG]	Num+1	mathematics
polymath [64]	[TG]	Num+1	mathematics
livemathbench [42]	[TG]	Num+1	mathematics

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

Benchmark	Eval	Method [CM]	Traits
conala [65]	[TG]	L-Shuff	coding

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

Benchmark	Eval	Method [CM]	Traits
afrimmlu direct amh [1]	[LL]	MC-FirstDistr	multilingual
afrixnli en direct amh [1]	[TG]	MC-FirstDistr	multilingual
arabic exams [24]	[LL]	MC-FirstDistr	multilingual
bangla mmlu [50]	[LL]	MC-FirstDistr	multilingual
basque glue [61]	[LL]	2C-Flip	multilingual
copa [56]	[LL]	2C-Flip	multilingual
global mmlu [59]	[LL]	MC-FirstDistr	multilingual
m mmlu [35]	[LL]	MC-FirstDistr	multilingual
m mmlu [35]	[LL]	2C-Flip	multilingual
noticia [21]	[LL]	Generic	multilingual
phrases ca-va []	[TG]	Generic	multilingual
wmt14 [6]	[TG]	L-Shuff	multilingual

Benchmark	Eval	Method [CM]	Traits
wmt16 [7]	[TG]	L-Shuff	multilingual

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

Benchmark	Eval	Method [CM]	Traits
babilong [32]	[LL]	MC-RandDistr	longcontext

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

Benchmark	Eval	Method [CM]	Traits
glianorex [23]	[LL]	MC-FirstDistr	medical

Table 8: Benchmarks (short names), evaluation abbreviations, contrastive method (short), and traits. Versions merged where applicable.

Benchmark	Eval	Method [CM]	Traits
wikitext103 [46]	[PPL]	LM-CorruptCont	general knowledge

323	B	Per-Task Results
324	C	Detailed Classification Results
325	D	Benchmark-Aided Steering Results
326	E	Optimal Sample Size Calculations
327	F	Fully Synthetic Generation
328	G	Agentic Capabilities