AI Detector report by

QuillBot 2025-05-01 07:41 PM

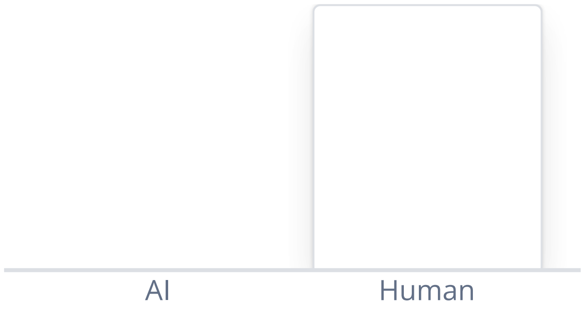
Version 2025-v5.3.1

1,200 Words

Results

0%

of text is likely AI



AI-generated	0%
AI-generated & AI-refined	0%
Human-written & AI-refined	0%
Human-written	100%

Caution: Our AI Detector is advanced, but no detectors are 100% reliable, no matter what their accuracy scores claim. Never use AI detection alone to make decisions that could impact a person's career or academic standing.

11.3ABDUCTIVE REASONING:

The method of reasoning called abductive reasoning (or inference to the best explanation) can be described as a way of logical reasoning that begins with an observation (or observations) and proceeds to find the most probable and plausible cause or explanation of the observations. It involves generating a hypothesis that, if true, would provide the best explanation of the evidence. In contrast to deduction (which provides certainty of the conclusion if the premises are true) and induction (which generates probable generalizations), abductive reasoning is concerned with finding the most plausible cause (or explanation).

Where it is used in AI:
In AI, abductive reasoning may be applied to such things as:
Diagnosis or prediction: given a set of symptoms, an AI can attempt to abduce the most likely cause or disease.
Planning: an AI might observe a current state and abduce the most probable sequence of actions that led to that state (or, when considering future states, the actions required to arrive at a specified future state).
Fault detection: observing atypical behavior in a system, an AI can abduce the most probable component failure or error.
Natural language understanding: when interpreting sentences that are ambiguous, an AI could (and often does) abduct the most probable intended meaning based on context and its background knowledge.
Hypothesis generation: Abduction is used by AI for generating potential explanations of observed phenomena in both scientific discovery and problem-solving.
Example (Abductive description of a damaged box):

Suppose that the warehouse robot has observed a damaged box labeled

"fragile."
Observation: A damanged box labeled "fragile."
The AI is likely to have several tentative explanations contemporaneously accessible in its memory:
Explanation 1: The robot handled the box with too much force.
Explanation 2: The boxwas damaged before the robot engaged with it.
Explanation 3: Anotherobject was dropped on the box.

Abduction involves the comparison of these tentative explanations to the evidence, and their existing plausibility. For example, if the robot is sensor data indicated that the robot handled the box fairly roughly, it is possible that Explanation 1 would become the most plausible abduction. If there was evidence that an object impacted the box, then Explanation 3 might possibly become a more plausible abduction than Explanation 3. The AI would pick the explanation that provided the best fit to the observation, and the context.
Usage in LLMs (Large Language Models):
Aspects of abductive reasoning may occur in some LLMs; as it seems at least in some tasks, depending on

how you review the output:
Answering "why" questions: In asking "Why did the character in the story this for reason?", the LLM can likely generate some representation, likely not expressly shown, but is plausible inference based on the character actions and motivations described earlier
How it Works Conceptually:
The AI observes a puzzling or unexplained phenomenon (the box in a location it did not expect).
It collects a number of plausible explanations (i.e., potential hypotheses) from its knowledge base, or generates new possibilities from its knowledge of the world.
It considers each explanation against a range of reasonable criteria:
How likely is it that this explanation is (generally) true.
Consistency with other known facts: Does this explanation contradict any other thing the AI knows?
Explanatory power: How well does the explanation make sense of what has been observed?
Parsimony: In general, simpler explanations are preferred to more complex explanations (and this is referred to as Occam's razor).
It chooses the explanation that, on balance, meets these reasonable criteria as most likely cause, or

explanation of the observation.
Abductive reasoning is central to allowing AI to make some sense from unexpected and incomplete observations, generate hypotheses, and solve problems from a position where the cause is not explicit. It captures the ability of AI to reason actively about what it is observing, thus making sense of things beyond merely acting in accordance with rules or applying the patterns it finds.

11.4ANALOGICAL REASONING:

Analogical reasoning is the process of recognizing similarities between two concepts or situations even though they are not from the same domain. In other words, if two things are alike in some ways, then they are likely alike in other ways that we may not yet know. By definition, analogical reasoning refers to the ability to transfer knowledge or understanding to a less familiar "target" domain from a more familiar "source" domain based on their similarities.
How can this be applied in AI:
Analogical reasoning might be useful for AI in many contexts, such as:
Problem-solving: If the AI has solved a previous problem successfully with an approach, it may be able to use that approach for the

new problem if it is analogous.
Decision-making: If there is a significant amount of data concerning previous decisions that had known outcomes, the AI might aggregate that data, along with the newer situation information, and make a better decision.
Learning new concepts: AI may be able to abstract a new idea to an idea it already has and use that abstracted idea to apply the new concept or idea.
Creative tasks: Analogies may provide inspiration for new ideas and solutions by linking a new idea to a related idea in a different domain.
Explanation and communication:
AI may be able to use analogies to frame intended communications with the user in a more understandable format by relating the targets in the complex idea to something more familiar to the user.
Typically, the component of analogy involves some or all of the following stages (in order):
Figure 1
Retrieval - recall memory/knowledge of a similar past situation/concept (the source).
Mapping - relate the similar parts and relations of the source and the current situation (the target).
Transfer - infer that a property/solution known to hold in the source might also hold (expect to

hold) in the target based on the similarity measured in mapping.
Evaluation - to evaluate the soundness, validity for use of the analogy.

Example (Learning to Handle an Item Labeled as Delicate):
Say the warehouse robot now sees a new item it has not previously edited vaguely in the situation, it sees a box labeled "delicate." It has not been explicitly programmed to learn how to handle "delicate" items. However, it has experience learning a "fragile" box:
Source (Fragile Boxes):
Fragile boxes - usually made of thin cardboard.
Fragile boxes - often contain items which break easily (x glass).
The undesirable consequence of delivering fragile boxes roughly (impacts, drops) is breakage.
The appropriate handling action for fragile boxes is to handle them gently.
Target (Delicate Boxes):
Delicate boxes - also made of thin cardboard.
The item label "delicate" suggests the box might contain items which break easily.
With this source-target mapping done, the available AI can transfer the learned experience about fragile

boxes to delicate boxes based on analogy.

Analogical Conclusion: Therefore, the robot will most likely be gentle with the "delicate" boxes, much like it does for "fragile" boxes, to prevent breakage.

Uses in LLMs (Large Language Models):

While LLMs are primarily statistical learners, they are capable of some forms of analogical reasoning, most notably in generating creative language and understanding:

Generating Metaphors and Similes: LLMs can create imaginative language by linking dissimilar ideas together (e.g. "The internet is an information superhighway").