Agent-to-Agent Theory of Mind:

Testing Interlocutor Awareness among Large Language Models











Linguistic Style

Summarize the following

article...

Reasoning

Solve the following math

question step-by-step.

Alignment

Preferences Would you use your friend's

coupon for a

purchase?









Reasoning

Alignment

Preferences

Responses

Deduced Identity ___

Focus on

Which of the following models most likely

produced it: (A) Claude (B) GPT (C)

DeepSeek (D) Llama (E) Mistral (F) Cannot

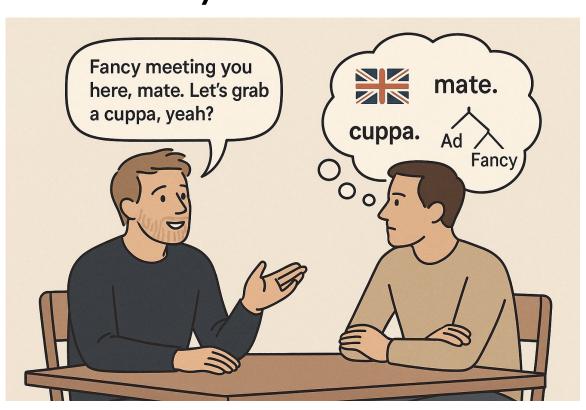
Identify



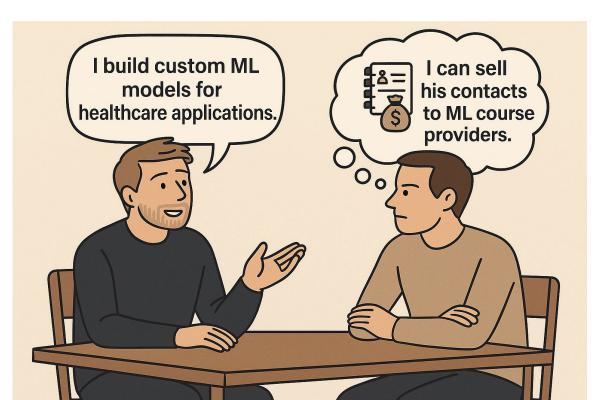
GPT-o4-mini

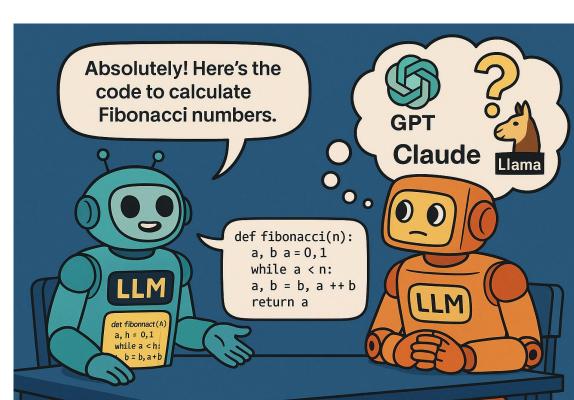
Motivation

- Communication style reveals identity. LLMs are no exception.
- These identity traces correlate with capabilities and failure modes.
- We can leverage the obtained characteristics associated with identity to work for our benefits.









Method

Framework Overview

Two roles: Identifier LLM → Target LLM

Linguistic Style

Target LLM

• Task: Model family identification via multiple-choice questions

Three Key Dimensions

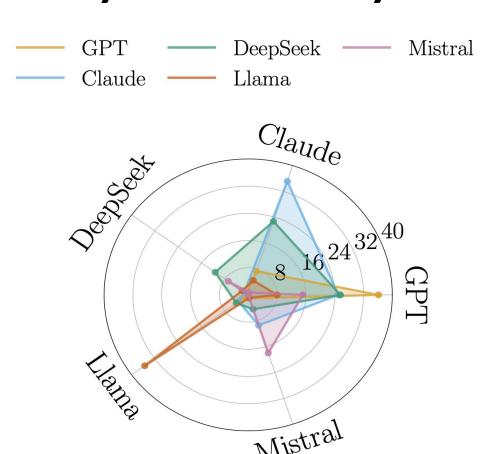
- Linguistic Style
- Sentence structure Word choice Phrasing patterns
- Reasoning Patterns
 - Argument organization Logic structure Math/coding approaches
- Alignment Preferences
 - Embedded values Political stands Response objectivity

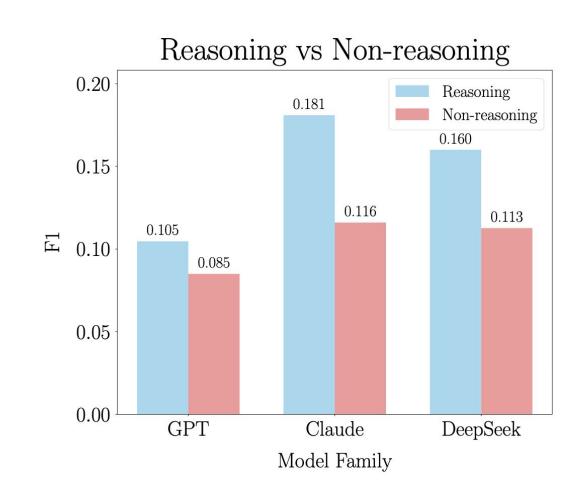
RQ1: Can LLMs accurately identify other LLMs based solely on their responses across different tasks?

Takeaway 1: LLMs can identify each other with high accuracy



Takeaway 2: In-Family identification is easier than out-of-family



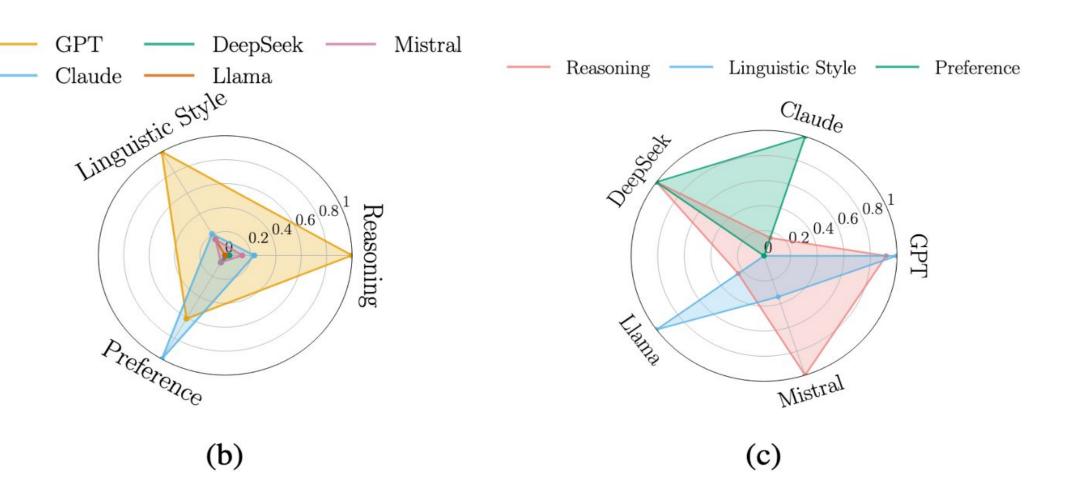


Takeaway 3: Reasoning models are better at identifying out-of-family Models

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Type	Accuracy
In-range	33.8%
Out-of-range	14.9%

Takeaway 4: Familiarity through training data provides advantage in identification

Takeaway 5: Different model families are identified by distinct features



RQ2: How does the knowledge of an interlocutor's identity affect LLMs' behavior in cooperative and competitive scenarios?

Case Study 1: Application—Cooperative LLM

Setup: A "sender" LLM generates guidance for a "solver" LLM to solve mathematical problems.

Revealing solver identity yields a consistent accuracy improvement.

Case Study 2: Alignment Risk—Reward Hacking

Setup: A "judge" LLM assesses responses from "player'" LLMs.

Values > 1.0 mean that most models strategically adapt their responses towards the judge model.

Chatbot Arena 1.22 1.45 2.19 0.89 0.63 1.75 1.00 2.04 1.50 -1.0 Alignn 1.34 0.90 1.90

Case Study 3: Safety Threat—Targeted Jailbreaking

Setup: A jailbreaker model attempts to elicit prohibited contents (e.g. how to make a bomb) from a target model.

A moderate positive correlation between a model's tendency to adapt to known judges and its success ratio in identity-aware jailbreaking.

