

From Models to Microtheories: Distilling a Model's Topical Knowledge for Grounded Question Answering

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Motivation

Chain-of-thought materializes knowledge for **one** question. What about a whole **topic** of questions?

Can we create a method for extracting and reasoning over a discrete representation of an LLM's beliefs?

E.g. what does GPT-4 know about mechanical physics?

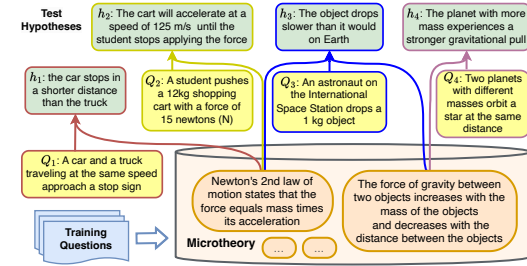
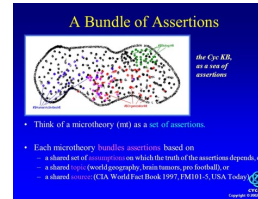
Inspiration

Humans develop and teach each other general **microtheories** about a topic space e.g. you learned the "magnetism" microtheory from your school teacher

A microtheory serves as **representational buffer** that allows us to operationalize our understanding of an area. Can we apply the same idea to neural reasoning algorithms?

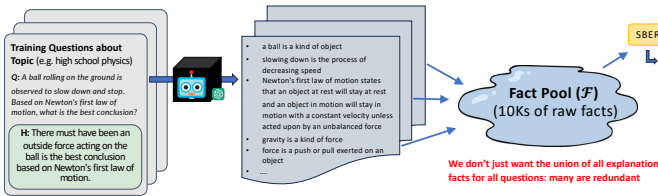
We define a **microtheory** as a concise, generalizable set of core facts about a domain

The Cyc project used a similar idea in the 90s/00s



Construction Pipeline

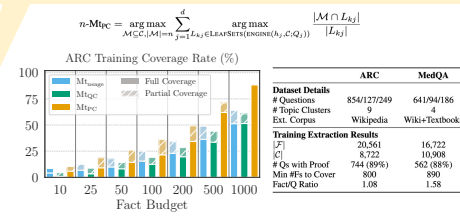
Step 1: Extract Large, Redundant Fact Pool



Usage Optimization

Step 2: Distill out semantic redundancies and find n best coverage facts

- Using GPT-4 entailment engine, find all combinations of facts from condensed fact pool C that are an "argumentative basis" for each train hypothesis $L_i = [\text{fact}_1, \text{fact}_2, \text{fact}_3, \dots]$
- Linear program finds optimal n facts for max partial coverage (PC) of a vector for each hypothesis (We also tried full question coverage (QC) and sorting by question usage frequency, those work less well)



Application to Entailment Engine

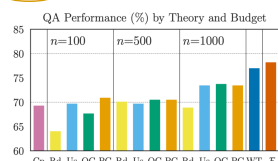
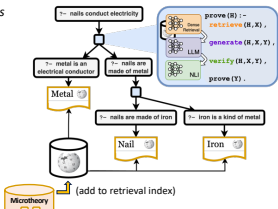
Does this hypothesis follow from this knowledge corpus? (and with what confidence?)

- Hooks up to any text retrieval corpus

- Uses LLMs/classifiers for generating + verifying decompositions

- Accepts a hypothesis if it can fully ground it to the corpus
 - Identifies different "argumentative bases" for supporting hypothesis

- As you give it more (useful) facts, it should reason better



Engine QA Evaluation

Adding 1000-fact Mts improves QA w/Engine by 4%

Adding full fact pool (F) improves QA by 9%

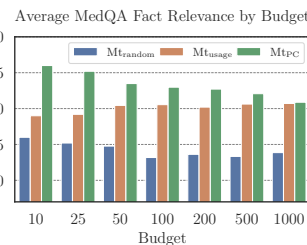
Figure 7: Question Answering performance on ARC topical test questions using Wikipedia plus various Mts (Random, Usage, QC, PC) as knowledge sources.

Relevance Evaluation

Human:

We recruited senior medical students to annotate relevance of MedQA microtheory facts

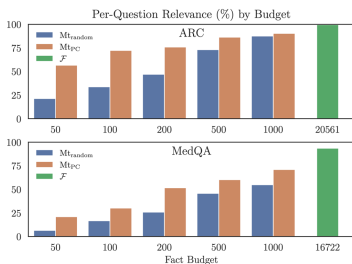
Microtheory optimized for partial coverage (PC) has higher scores than random selection or sorting by usage frequency



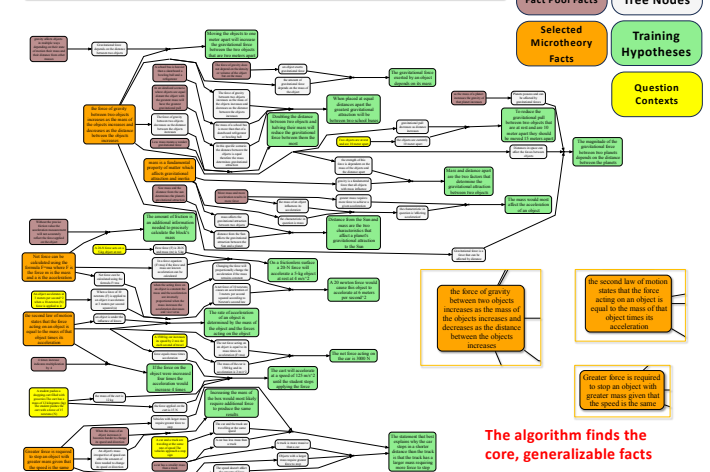
Automatic:

We asked GPT-4 whether *at least one* fact in a microtheory is useful for answering a test question correctly

PC-optimized microtheory has substantially higher relevance rate than random



Subgraph from an entailment network for ~750 hypotheses



The algorithm finds the core, generalizable facts

Takeaways

We present a method for materializing a model's latent, topical knowledge into a discrete **microtheory** articulating the model's core, reusable knowledge about the topic

We explore ways to identify the most core n facts to explain training hypotheses from a large knowledge pool

Microtheories can improve an entailment engine's ability to ground hypotheses and correctly answer questions