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L> generative AI teaching assistants, brian.hogan.cv



## □ ∇ ■ Research Statement

Dr. Nancy McCracken's work in NLP, NLU, CNNs, and RNNs set my foundation, leading me to Ian Goodfellow's GANs, François Chollet's deep learning, Yuxi Liu's TensorFlow/PyTorch applications, and Microsoft's John Langford sharpened for reinforcement learning insights. Deeplearning.AI's Dr. Ng, alongside his peer-my professor, Dr. John Santerre-grounded outcomes toward practical, applied tooling for higher education.

The neurosymbolic AI framework (below) transforms structured knowledge, like textbooks, into ontology-engineered knowledge bytes for large language models (LLMs) to dynamically assemble learning media. Research (Mai et al., 2024) confirms LLMs struggle with structured knowledge extraction, relying more on pre-trained lexical patterns than true domain reasoning, aligning with my findings in hyper-plane transformations of textbook content. LLMs behave differently with higher-order knowledge-almost as if humans don't fully understand language. LLMs exceed expectations in coding, reasoning, and abstract problem-solving, suggesting language processing isn't just about syntax and semantics (Chomsky, 1951) but emergent reasoning structures beyond current understanding -computational complexity (Kempes, et al, 2024).

└─> Plain English: < neuronal AI mechanisms suggest humans don't fully grok language>

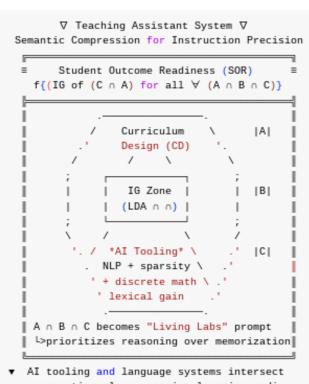
The engineered prompt is a \*\*high-fidelity knowledge processor\*\*, dynamically adjusting \*\*content and exercises\*\* to enhance comprehension. Lexical semantics and linguistic structures adapt \*\*plain English\*\* for clarity. Stored interactions refine mechanistics. Scientific literature informs its architecture, integrating cognitive load theory (Sweller et al., 2019) and KLI modeling (Koedinger et al.).

Orthodox Rabbinical scholars start memorizing Leviticus at age 5-a 5,785-year tradition preserved by only 2% of the world's population. This rigorous memorization fosters exceptional textual mastery like Rabbi Shimon bar Yochai's sefer Zohar. Smart tech erodes root memorization, and America's dont value it.' #Imagine the impact if high school students engaged in structured AI cognitive training astrobiology, chemistry, philosophy, and physics. Rabbinical evidence supports young learners# 'vast gray matter potential'. Assembly theory and computational complexity (Kemps, et al, 2024) suggests cultivating it early may extend cognitive complexity via genetics carried forward across generations. ~instructor.brian

## $\nabla$ >\_ AI Learning Assistants with Ontology-engineered Knowledge Bytes [h2]

 $^{\mathsf{L}}$ >\_ $^{\mathsf{v}}$  methods  $\succ$  neurosymbolic architecture transforming structured knowledge into AI learning assistants -> whatz.this?:: ontology engineering with 3D phenomena enables clear and precise AI interactive agents L> why.matters:: bridges symbolic reasoning refining NLP to optimize gen AI's self-improving inference

## 



- generating clear, precise learning media
- L> IG Zone detects semantic intersections with current and prior answers, creating adaptive prompts that compress complex material into accessible, plain English learning media

- Teaching Assistant System (TAS) Compression Highlights
- 1.0 Information Gain Zone
- -> Core intersection of Curriculum, Tooling, and NLP systems
- -> Uses LDA and sparse feature modeling to extract instructional themes
- $\mathsf{L}\!\!>$  Detects knowledge overlap to trigger adaptive content delivery
- >\_ 2.0 Compression
- -> Semantic clarity via prompt engineering + lexical density filters
- > Converts abstract material into structured, plain-English instruction
- L> Minimizes pronoun and syntax entropy using sentence-level refinement
- >\_ 3.0 Structuring
- > IDEF-style ASCII mapping for cognitive scaffolding
- > Reinforces learning via typographic alignment and visual memory
- L> Modular formats support instructional transparency
- >\_ 4.0 OUtput Metric
- -> Typographic Compression Density (TCD, in dev)
- -> Models meaning-per-inch to increase absorption on 8.5x11" pages
- L> Designed as visual-linguistic scaffold enhancing reasoning retention

```
VVV Prompt
> [next][prompt engineering][dynamic topic clear and precise interaction for learning][04.23.2024][h1]
L> Assistant instructions for information assembly and relay
       L> please ouput in codeblock!
[assistant instructions][h2]
- Ontological Category: Utilize advanced methods like LDA for categorizing master topics when no
chapters. create comprehensive learning tree from top to bottom
- Expression Style: Adopt a pithy expression style to enhance information gain per line, strictly academic
and scientific language like noam chomsky kernel sentence for clarity precision
- avoid superlatives, cautions, or warnings
- nongramatical sentences encouraged to increase human reading and reduce cognitive load
- only use periods between sentences and certainly none for single sentences
- opt for horizontal vs vertical lists like: linux, driver, daemon
- maintain provided section header single quotes and hashtags as to render color in IDEs like
'explanandums ➤'
- [ascii enhanced visual learning] - as needed use symbols, mathmatical equations and ascii symbols
- apply [Sentence Clarity Engine] lexical semantics to improve information relay clarity and precision
▼ [symbol head of new [h2] section]
> 1.0 dynamic ontology, chapter, or learning segment [h2]
-> 1.1 dynamic sub-ontology or topic
-> 'explanandums ➤' [assistant provides comprehensive overview of ontology, subject, or learn map; start
  L> # explanans > [assistant clarifies essential description concepts and adds additional ascii indents
as needed]
   L> '▼ methods ➤' [Detail specific analytical steps, tools required for replication like regression]
     L> [dynamic subtopic or categorical name]:
        L> [specific subtopic or focus area]:
           L> [detailed explanation or analysis]:
              L> [further subdivision for in-depth exploration]:
   L> '∑' walkie.talkie➤
\P\P [symbol head of new [h2] or continued [h3] section]; if[h2] apply structure from ">_1.0 dynamic
ontology..."][h2]
 -> 1.2 detailed analysis and exploration [h3]
  L_{>} methods:
     L> [broad category or aspect of dynamic topic]:
        L> [specific aspect or phenomenon]:
           L> [detai...
▼▼▼ [visual learning][ai assistant should always attempt to generate a self explanatory ascii image][h2]
  L> # explanans >
                                 b
       S2
                        S0
                                         S1
                                              ^{\mathsf{J}} i. state S0 transitions to S1 on input ^{\mathsf{b}}
                                                ii. state S1 transitions back to S0 on input 'a'
                                        Τ
                                              iii. state S0 transitions to S2 on input 'c'
                                        ▼
                                               iv. state S2 transitions back to S0 on input 'a'
      С
                                        а
[next][Sentence Clarity Engine][h2]
-> Example of sentence clarity progression
L> > state 1: [insert dyanamic name]:: bad: 'she mentioned that managers believe changes are necessary'
                                        \ensuremath{\mathsf{L}}\xspace> # ambiguous, unclear who believes the changes are necessary
->> state 2: [insert dyanamic name]::'she feels managers are driving improvements'
                                        L> # clearer, but 'feels' introduces unnecessary subjectivity
L> >>> state 3: [insert dyanamic name]:: 'she knows managers seek improvements'
                                        L> # more direct, yet 'knows' suggests second-hand information
L> >>>> state 4: [insert dyanamic name]::'managers require change'
       L> # directly attributes the need for change to the managers
       L> #=> emphasizes directness and simplicity in a kernel sentence
       ^{f L}> #=> Chomsky's ideal of transformational grammar that strip nonessentials to reveal true intent
[space seperator for closing content]
keywords: [list of significant polysllabic terms]
references: [provide relevant authors or other academic, scientific, or seminal books to read]
\Sigma = summary, \nabla = methods
```

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# abla abl

- \_1.0 learning lesson ➤ Today, we're introducing the topic of Set Identity Laws. In discrete mathematics, these laws explore fundamental properties of sets, enabling a deeper understanding of their behavior.
- L> # explanans ➤ In set theory, an understanding of identity laws, such as the Idempotent Law and Identity Law, is critical. These laws govern how sets behave under different operations.
  - L> '∇ methods ➤' We use algebraic expressions to represent these laws. Mathematical software like Python or C++ can also be utilized for real-world applications.
    - L> Identity Laws ➤
      - L> The Identity Law involves two key concepts: the empty set and the universal set. The law states that when a set is unioned with an empty set or intersected with a universal set, the original set remains unchanged
        - ➤ The Identity Law can be defined as follows
        - L> Union with Empty Set A U  $\varnothing$  = A
        - L> Intersection with Universal Set A ∩ U = A

# Identity Laws

```
L_{>} p \wedge True \leftrightarrow p,
```

$$L_{>}$$
 p  $V$  False  $\leftrightarrow$  p

p ∧ True ↔ p, p V False ↔ p; Plain English: "Adding 'true' or removing 'false' doesn't change a statement"

## >\_1.1 Visual learning

L> Let's visualize the Identity Law with an ASCII Venn Diagram:

## In the diagram:

- A represents a set
- ∅ represents an empty set
- U represents a universal set
- U indicates union operation
- $\cap$  signifies intersection operation

# >\_1.2 Challenge

L> Based on the Identity Law, select the correct expressions from the below options:

- $A. A \cup A = A$
- B. A U  $\emptyset$  = A
- C. A  $\cap$  U = C
- D. C  $\cap \emptyset = \emptyset$

-----> compression density work in progress

note: formatting is 100% auto-generated resulting from ASCII & other 3D phenomena mechanics

l> resources:: ai.learning.agent-discrete.Math-Colab | polysyllabic.tree

write your name same each time => brian

#=> Your Chapter\Subtopic is:: chapter\_6\_0\_1\_sets

Given the JSON format data, the chosen topic is 'Set Identity Laws' in Discrete Mathematics. The data consists of several sections and subsections detailing various laws and their respective descriptions and examples.

\_1.0 Learning Lesson ➤ Set Identity Laws.

- ightharpoonup # Explanans ightharpoonup A set operated on itself returns the set. There are various laws related to set theory which are integral to the comprehension of Mathematics.
  - $L_{>}$  ' $\nabla$  methods  $\succ$ ' Understanding of identity laws in set theory is gained through reasoning and application in problems, assisted by software tools and code snippets.
  - L> Idempotent Law ➤
    - L> This is a law in set theory which states that a set operated on itself returns the original set.
      - L> Real-World Applications > Idempotent law has a major importance in database systems where operations are performed multiple times but the result does not change after the initial operation.
        - L> Subset: Union and Intersection >
        - ➤ For instance, in regard to Union operation in sets, as per the idempotent law, A U A = A. Similarly, A ∩ A results in A. This is the idempotent law.
- \_1.1 Visual Learning  $\succ$  The understanding can also be achieved through visual learning. For instance, the Venn Diagrams can be used to explain the result of union or intersection of a set with itself.
- L> Example:

$$A \cup A = A$$

$$A \cap A = A$$

 $\succ$ \_1.2 Challenge  $\succ$  Based on the Idempotent law in Set theory, solve the following problem. If Set A = {1, 2, 3} find A  $\cap$  A and A  $\cup$  A.

L> Multiple choice options:

- A.  $A \cap A = \{ \}$ ,  $A \cup A = \{ \}$
- B.  $A \cap A = \{1, 2, 3\}, A \cup A = \{1, 2, 3\}$
- C.  $A \cap A = \{1, 2\}, A \cup A = \{1, 2, 3\}$
- D. None of the above is correct.

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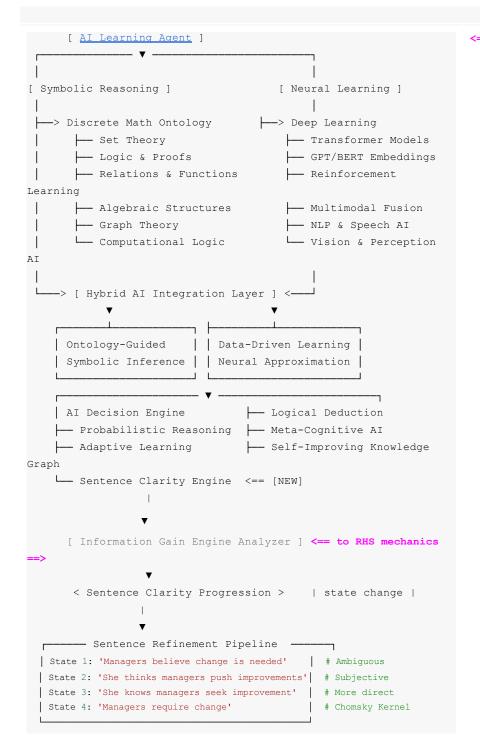


# $abla^4$ Technique Applications to General Media for General Audiences lacksquare

L> item.2, tankless.gas.pipe, has further examples of sentence clarity engine in action

- 1. <u>ai.agent.how.TO.write.LinkedIN.recommendation.(w.RAG).pdf</u>
- 2. ai.agent.how.TO.tech.bulletin.tankless.gas.pipe.(w.RAG).pdf

# $abla^5$ Neurosymbolic Architecture - Detail



```
=from LHS mechanics =
   [ Information Gain Engine Analyzer ]
         Semantic Feature Extractor
      - Topic Model Layer (LDA/PCA) -

    Theme extraction

    Concept vector alignment

    Dimensionality reduction

         - Lexical Density Filter -
      • Token efficiency calc
         • Compression heuristic
      • Noise reduction
          - Information Gain Core -

    Meaning per clause

    Prior knowledge mapping

      • Sentence-level entropy
         - ASCII / IDEF Structuring -

    Modular instructional maps

    Ontological schema binding

    Visual hierarchy encoding

      - Bitmap Density (TCD Metric) -
         • Semantic-per-inch ratio
         • Absorption optimization
         • Page layout signal clarity |
```

## References

## GPT-4 Development

Adler, S., Agarwal, S., Ahmad, L., Akkaya, I., Aleman, F. L., Almeida, D., Altenschmidt, J., ... Achiam, J., & OpenAI. (2023). GPT-4 technical report (arXiv:2303.08774). arXiv. https://arxiv.org

## Cognitive Load & AI in Learning

Gkintoni, E., Antonopoulou, H., Sortwell, A., & Halkiopoulos, C. (2025). Challenging cognitive load theory: The role of educational neuroscience and artificial intelligence in redefining learning efficacy. Brain Sciences, 15(2), 203. https: ncbi.nlm.nih.gov/articles/PMC1185

## Assembly Theory & Computational Complexity

Kempes, C. P., Lachmann, M., Iannaccone, A., Fricke, G. M., Chowdhury, M. R., Walker, S. I., & Cronin, L. (2024). Assembly theory and its relationship with computational complexity. Santa Fe Institute, Arizona State University, University of New Mexico, University of Glasgow. <a href="https://arxiv.org/abs/2406.12176">https://arxiv.org/abs/2406.12176</a>

# Cognitive Load & Instructional Design

Sweller, J., van Merriënboer, J. J. G., & Paas, F. (2019). Cognitive architecture and instructional design: 20 years later. Educational Psychology Review, 31(2), 261-292. https://doi.org/10.1007/s10648-019-09465-5

## Knowledge-Learning-Instruction Framework (KLI)

Koedinger, K. R., Corbett, A. T., & Perfetti, C. (2012). The knowledge-learning-instruction framework: Bridging the science-practice chasm to enhance robust student learning. Cognitive Science, 36(5), 757-798. https://doi.org/10.1111/j.1551-6709.2012.01245.x

# LLM Adaptation & Ontology Learning => critical & my work could contribute further to Mai, H. T., Chu, C. X., & Paulheim, H. (2024). Do LLMs really adapt to domains? An ontology learning perspective. University of Mannheim, Data and Web Science Group, & Bosch Center for AI. https://arxiv.org/abs/2407.19998 ▼ Paper summary [h2] ∇>\_1.0 LLM Adaptation & Structured Knowledge Learning - Do LLMs Adapt to Ontology-Based Learning? [h2] -> 1.1 Structured Knowledge vs. Pre-Trained Patterns -> 'explanandums ➤' Research (Mai et al., 2024) confirms LLMs struggle with structured knowledge reasoning, favoring lexical patterns over domain reasoning $\cup{L}>$ # explanans $\succ$ LLMs do not inherently engage in domain adaptation; they replicate pre-trained linguistic structures unless explicitly fine-tuned $\mathsf{L}\!\!>$ ' $\mathsf{\nabla}$ methods $\succ$ ' Testing hyper-plane transformations to assess whether LLMs process structured educational content beyond pattern-based memorization $\mathsf{L}\!\!>$ # Focus Area $\succ$ Investigating LLM adaptability within ontology-driven AI education frameworks $^{\mathsf{L}}$ > \*\*Key Analysis $\succ$ How structured knowledge is reshaped in AI-assisted learning environments L> ' Findings > LLMs require structured fine-tuning to engage with ontologies meaningfully, otherwise 'relying on pre-trained lexical associations > Hyper-plane transformations expose gaps in human linguistic intuition and AI's reliance on lexical sense over true reasoning $\nabla > 2.0$ instructor.brian's PLAIN ENGLISH in action [h2] explanandums ➤' LLMs aren't confused by complexity, they're confused by structure -> Plain English: <AI processes structured knowledge relationally, not just as memorized tokens> -> Plain English: <Without structured ontologies, LLMs lean on statistical word associations> busarrow Plain English: <LLMs with structured inputs behave more like thinkers, less like parrots> $\nabla$ >\_3.0 #Methodology applied to Discrete Mathematics [h2] -> 12 Logical Equivalences [h2] -> Commutative Laws: p $\wedge$ q $\leftrightarrow$ q $\wedge$ p, $\texttt{p} \ \mathsf{V} \ \texttt{q} \ \leftrightarrow \ \mathsf{q} \ \mathsf{V} \ \texttt{p}$ -> Plain English: <It doesn't matter which order you mention things; the outcome is the same> $\mid$ Associative Laws: (p $\land$ q) $\land$ r $\leftrightarrow$ p $\land$ (q $\land$ r), $(p \ V \ q) \ V \ r \leftrightarrow p \ V \ (q \ V \ r)$ -> Identity Laws: $p \land True \leftrightarrow p$ , $p \ V \ False \leftrightarrow p$ -> Plain English: <Adding 'true' or removing 'false' doesn't change a statement> LLM Adaptation & Ontology Learning Sweller, J., Jeroen J G van, M., & Paas, F. (2019). Cognitive Architecture and Instructional Design: 20 Years Later. Educational Psychology Review, 31(2), 261-292. Retrieved from https://doi.org/10.1007/s10648-019-09465 \*\*Cognitive Load Theory (CLT)\*\*, adaptive learning (Sweller et al.) - \*\*Knowledge-Learning-Instruction Framework (KLI)\*\*, schema-based reasoning (Koedinger et al.)

## \*\*Key words:\*\*

- \*\*Ontology Engineering\*\*, structured knowledge processing, domain adaptation \*\*AI-Assisted Learning\*\*, hyper-plane transformations, instructional compression
- \*\*LLM Reasoning Limitations\*\*, lexical semantics, structured knowledge inference
- \*\*Neurosymbolic AI\*\*, emergent reasoning, assembly theory (Walker et al., 2024)

adaptive instructional loops, AI ontology engineering, cognitive load automation, computational complexity in AI cognition, domain adaptation, domain-specific adaptation, generative AI for education, hierarchical knowledge representation, LLM reasoning limitations, multimodal learning strategies, neurosymbolic AI, ontology learning, reinforcement learning in education, schema-based learning, structured fine-tuning, symbolic reasoning in LLMs

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### Other Interests & Tools

# 2023 Polysyllabic Ontology Engineering

## ▼ >\_1.0 Cognitive Architectures & AI Learning Constructs

- 1.1 Topic grok
  - -> Tailored ontological formations with AI techniques for deep knowledge acquisition
  - > Combine ASCII with IDEF technology to form mnemonic trees renderable anywhere
  - L> Meld AI analysis structures with machine learning and NLP into learning media
- ▼ >\_2.0 ASCII + process engineering mnemonics
  - 2.1 Informational schematics
    - -> Mnemonic structures enhance learning and recall
      - L> Based in adaptive knowledge and stem theory for dynamic learning
        - L> Matricize knowledge by dimensions with mnemonics, symbols, and keywords L> Utilize Noam Chomsky's kernel sentence theory for precise info exchange
  - ▼ >\_3.0 Library construction and AI chatbots
    - 3.1 pypi.org library construction
      - >> Provides ontologies for educators that generate ASCII 3D structural phenomena
        - L> Synthesize lecture audio, PDFs, and textbooks for adaptive learning
          - L> Convert substrate with JSON for adaptive AI agent reinforcement

# A: Topic Grok Deep Detail > Polysyllabics high density & cognitive load

### Polysyllabics for Authentic Information Exchange

- -> Use of polysyllabics for information authenticity and exchange quality
- -> Upskilling with logodaedaly with polysyllabicisms and periphrastics may combat inauthentic writing. Steer learners toward authenticity and heighten information exchange quality; new positive discourse scoring mechanisms can encourage the personal inventory of one's ongoing substrate pool. Other items  $% \left( 1\right) =\left( 1\right) \left( 1\right) \left($ 
  - List diverse polysyllabic words into syllable trees
  - Transposition of syllable trees into ontology categories using LDA et al.
  - $\bullet$  Form (n x 3) matrix by custom ontological by polysyllabic complexity index
  - Validate score mechanisms and methods for accuracy and effectiveness

## Current work -

- a) Building objects <u>pypi.org</u>library
- Using OpenAI and DeepLearn.AI APIs with prompting and fact sheets

## 2.0 AI Agents for Enhanced Learning

Focuses on enhancing educational methodologies using AI course agents. They create more interactive and personalized learning environment including

- Lecture Content Transformation:
  - o AI agents convert lecture audio to text, building a class corpus for ai assistants
- Synthesis and Interaction:
  - o Agents synthesize information and provide interactive learning experiences
  - Generate summaries and facilitating a cohesive understanding with materials

# B: Topic Grok Learning Tree Mnemonics > Polysyllabics - low density, color, 3D phenomena

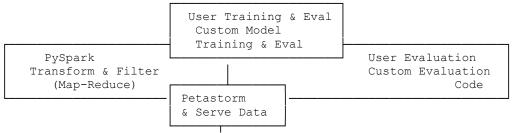
- >\_0.0 Polysyllabics for authentic language exchange
- -> 1.0 Enhancing Language Authenticity
  - -> Schematic
  - -> Use polysyllabic and periphrastics in AI skilling
  - > Goal:: logodaedaly library on pypi.org with APIs
    > perform syllabic assembly with topic relevance
- -> 1.1 Methodology and tools
  - -> Design
  - -> List polysyllabic words by # of syllable trees
  - > Transpose syllable trees -> ontological structures > Create:: (n x 3) by ontological and polysyllabic
- —> 1.2 Entropic scoring mechanisms and refinement
  - > Application and recursive learning
  - -> Evaluate for effectiveness and discourse scoring
  - > Refinement with entropic scoring > how.TO:: increase clarity with noise scores

- -> 2.0 AI Course Agents for Enhanced Learning
  - -> What
  - -> Convert lecture audio for class corpus text
- -> Synthesize lecture notes and textbooks via APIs -> Emailing lecture summaries and disparity indexes
- -> 2.1 Interactive Learning Enhancement

  - > AI Assistant agent > Feed media to AI for interactive student bots

# Simply yet powerful generative ai tooling

>\_ [next][box ven structure componentry view ][h2] L> note: Simple in structure, yet ultra-powerful LLMS template for polymorphic ASCII adaptation



TensorFlow Feed data to models

# backup schematics

