

>_ [next][prompt engineering][dynamic topic clear and precise interaction for learning][04.23.2024][h1]

↳_Assistant instructions for information assembly and relay

↳_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
- nongrammatical 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 this line]

↳_# explanans > [assistant clarifies essential description concepts and adds additional ascii indents as needed]

↳_ '▼ methods >' [Detail specific analytical steps, tools required for replication like regression]

↳_ [dynamic subtopic or categorical name]:

↳_ [specific subtopic or focus area]:

↳_ [detailed explanation or analysis]:

↳_ [further subdivision for in-depth exploration]:

↳_ 'Σ' walkie.talkie>

▼▼ [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]

↳_ methods:

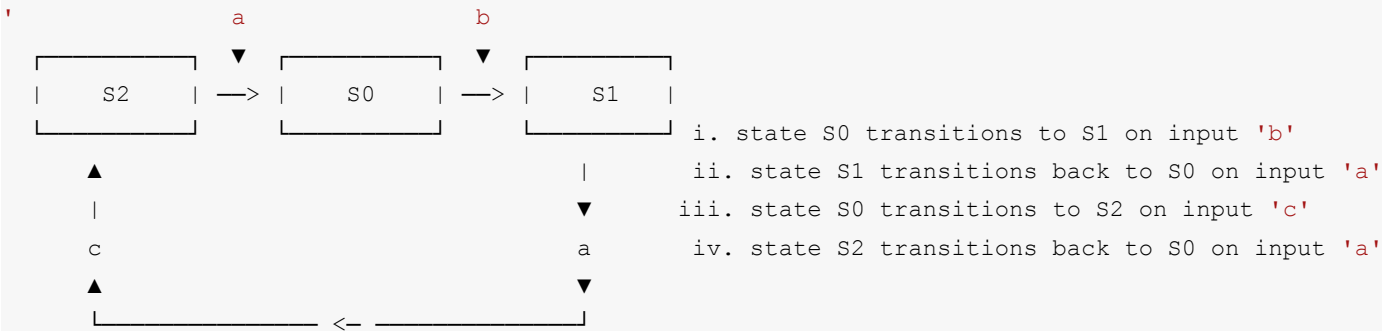
↳_ [broad category or aspect of dynamic topic]:

↳_ [specific aspect or phenomenon]:

↳_ [detai...

▼▼▼ [visual learning][ai assistant should always attempt to generate a self explanatory ascii image][h2]

↳_# explanans >



[next][Sentence Clarity Engine][h2]

-> Example of sentence clarity progression

↳_> state 1: [insert dyanamic name]:: bad: 'she mentioned that managers believe changes are necessary'

↳_↳_# ambiguous, unclear who believes the changes are necessary

↳_>> state 2: [insert dyanamic name]::'she feels managers are driving improvements'

↳_↳_# clearer, but 'feels' introduces unnecessary subjectivity

↳_>>> state 3: [insert dyanamic name]:: 'she knows managers seek improvements'

↳_↳_# more direct, yet 'knows' suggests second-hand information

↳_>>>> state 4: [insert dyanamic name]::'managers require change'

↳_↳_# directly attributes the need for change to the managers

↳_↳_#=> emphasizes directness and simplicity in a kernel sentence

↳_↳_#=> Chomsky's ideal of transformational grammar that strip nonessentials to reveal true intent

[space seperator for closing content]

keywords: [list of significant polysyllabic terms]

references: [provide relevant authors or other academic, scientific, or seminal books to read]

Σ = summary, ▼ = methods



▽ ▽ ▽ ▽ ▽ Exmple Outcome 1 - Discrete Mathmatics

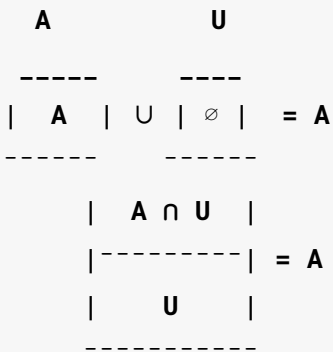
- _1.0 learning lesson ➤ Today, we're introducing the topic of Set Identity Laws. In discrete mathematics, these laws explore fundamental properties of sets, enabling a deeper understanding of their behavior.
- ↳ # explanans ➤ In set theory, an understanding of identity laws, such as the Idempotent Law and Identity Law, is critical. These laws govern how sets behave under different operations.
- ↳ '▽ methods ➤' We use algebraic expressions to represent these laws. Mathematical software like Python or C++ can also be utilized for real-world applications.
- ↳ Identity Laws ➤
- ↳ 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
 - ↳ Union with Empty Set - $A \cup \emptyset = A$
 - ↳ Intersection with Universal Set - $A \cap U = A$

Identity Laws

- ↳ $p \wedge \text{True} \leftrightarrow p$,
- ↳ $p \vee \text{False} \leftrightarrow p$
- $p \wedge \text{True} \leftrightarrow p$, $p \vee \text{False} \leftrightarrow p$; Plain English: "Adding 'true' or removing 'false' doesn't change a statement"

>_1.1 Visual learning

- ↳ 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
 - ∩ signifies intersection operation

>_1.2 Challenge

- ↳ Based on the Identity Law, select the correct expressions from the below options:
- A. $A \cup A = A$
 - B. $A \cup \emptyset = A$
 - 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

- ↳ 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.
  L> # Explanans > 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> '▽ methods >' 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 ∪ A
      = A. Similarly, A ∩ A results in A. This is the idempotent law.

>_1.1 Visual Learning > 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 ∪ A = A

                                ┌───┐
                                │   │
                                │ A │
                                │   │
                                └───┘

                                A ∩ A = A

                                ┌───┐
                                │   │
                                │ A │
                                │   │
                                └───┘

>_1.2 Challenge > Based on the Idempotent law in Set theory, solve the following problem. If Set A = {1,
2, 3} find A ∩ A and A ∪ A.

L> Multiple choice options:
  A. A ∩ A = { }, A ∪ A = { }
  B. A ∩ A = {1, 2, 3}, A ∪ A = {1, 2, 3}
  C. A ∩ A = {1, 2}, A ∪ A = {1, 2, 3}
  D. None of the above is correct.
```

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

L> resources:: [ai.learning.agent-discrete.Math-Colab](#) | [polysyllabic.tree](#)

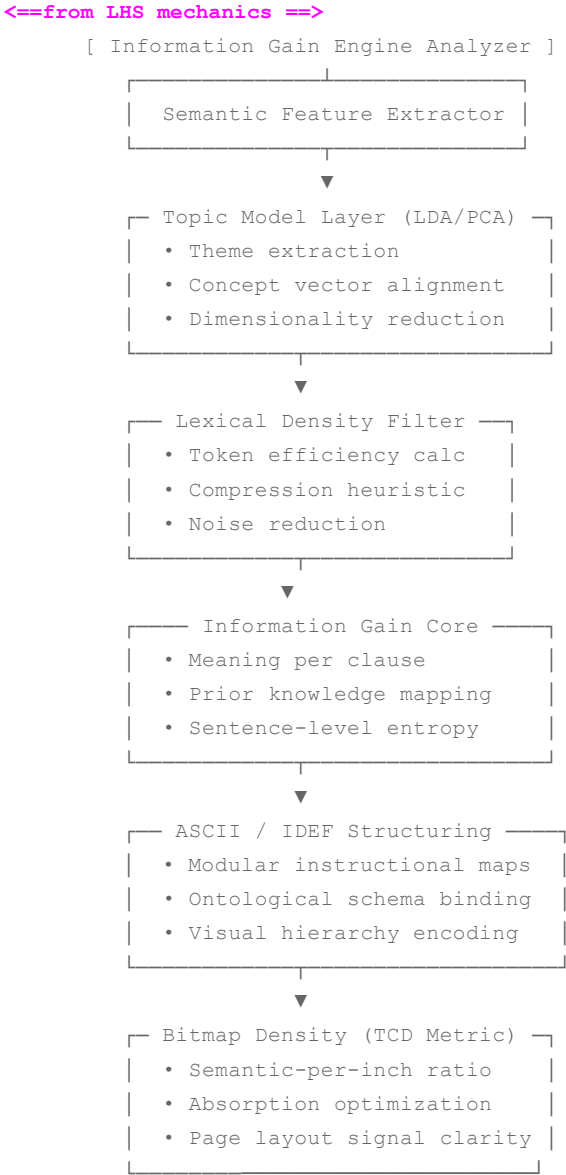
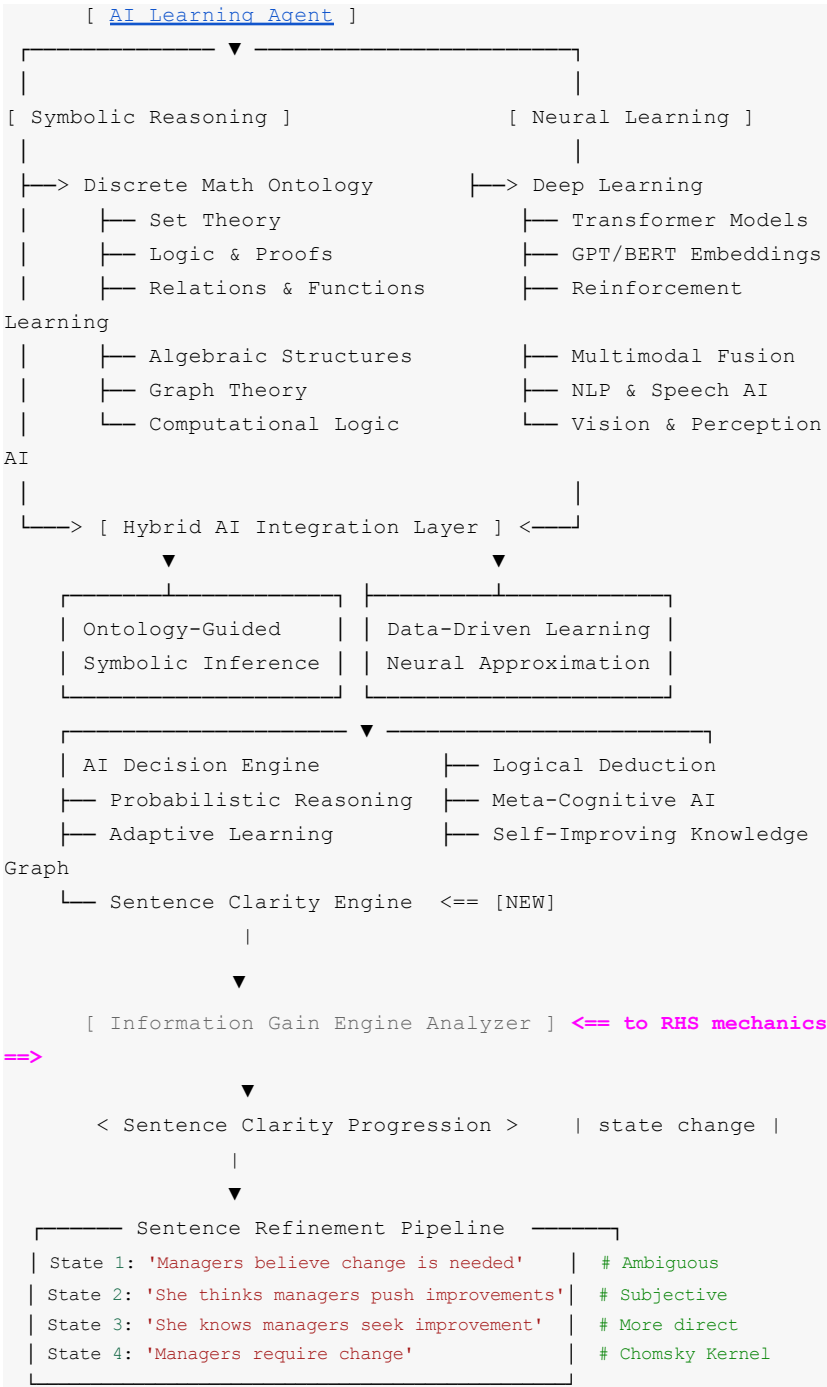


▽⁴ Technique Applications to General Media for General Audiences

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

- 1. [ai.agent.how.TO.write.LinkedIN.recommendation.\(w.RAG\).pdf](#)
- 2. [ai.agent.how.TO.tech.bulletin.tankless.gas.pipe.\(w.RAG\).pdf](#)

▽⁵ Neurosymbolic Architecture - Detail



References

GPT-4 Development

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

Cognitive Load & AI in Learning

Gkintoni, E., Antonopoulou, H., Sortwell, A., & Halkiopoulous, C. (2025). Challenging cognitive load theory: The role of educational neuroscience and artificial intelligence in redefining learning efficacy. Brain Sciences, 15(2), 203. <https://pmc.ncbi.nlm.nih.gov/articles/PMC11852728/>

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. <https://arxiv.org/abs/2406.12176>

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
    L> # explanans > LLMs do not inherently engage in domain adaptation; they replicate pre-trained linguistic
        structures unless explicitly fine-tuned
    L> '▽ methods >' Testing hyper-plane transformations to assess whether LLMs process structured
educational
        content beyond pattern-based memorization
    L> # Focus Area > Investigating LLM adaptability within ontology-driven AI education frameworks
        L> **Key Analysis > 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

▽>_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>
    |> Plain English: <Hyperplane scaffolding forces AI to reason through structure, not mimic words>
    L> Plain English: <LLMs with structured inputs behave more like thinkers, less like parrots>

▽>_3.0 #Methodology applied to Discrete Mathematics [h2]
    |>_12 Logical Equivalences [h2]
    |> Commutative Laws:  $p \wedge q \leftrightarrow q \wedge p$ ,
    |    |
    |    |  $p \vee q \leftrightarrow q \vee p$ 
    |    L> Plain English: <It doesn't matter which order you mention things; the outcome is the same>
    |
    |> Associative Laws:  $(p \wedge q) \wedge r \leftrightarrow p \wedge (q \wedge r)$ ,
    |    |
    |    |  $(p \vee q) \vee r \leftrightarrow p \vee (q \vee r)$ 
    |    L> Plain English: <How you group things together doesn't change the result>
    |
    |> Identity Laws:  $p \wedge \text{True} \leftrightarrow p$ ,
    |    |
    |    |  $p \vee \text{False} \leftrightarrow p$ 
    |    L> 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/s10648-019-09465-5>

****Key words:****

- ****Cognitive Load Theory (CLT)****, adaptive learning (Sweller et al.)
- ****Knowledge-Learning-Instruction Framework (KLI)****, schema-based reasoning (Koedinger et al.)
- ****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



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
- ↳ 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
 - ↳ Based in adaptive knowledge and stem theory for dynamic learning
 - ↳ Matricize knowledge by dimensions with mnemonics, symbols, and keywords
 - ↳ Utilize Noam Chomsky’s kernel sentence theory for precise info exchange

>_3.0 Library construction and AI chatbots

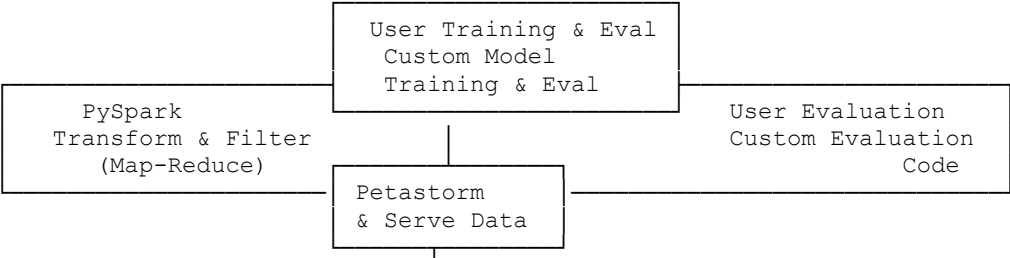
3.1 pypi.org library construction

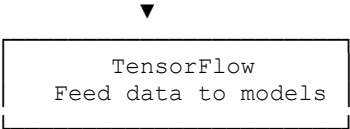
- ↳ Provides ontologies for educators that generate ASCII 3D structural phenomena
 - ↳ Synthesize lecture audio, PDFs, and textbooks for adaptive learning
 - ↳ Convert substrate with JSON for adaptive AI agent reinforcement

A: Topic Grok Deep Detail > Polysyllabics - high density & cognitive load	B: Topic Grok Learning Tree Mnemonics > Polysyllabics - low density, color, 3D phenomena
<p>Polysyllabics for Authentic Information Exchange</p> <p>→ Use of polysyllabics for information authenticity and exchange quality</p> <p>→ 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</p> <ul style="list-style-type: none">• List diverse polysyllabic words into syllable trees• Transposition of syllable trees into ontology categories using LDA et al.• Form (n x 3) matrix by custom ontological by polysyllabic complexity index• Validate score mechanisms and methods for accuracy and effectiveness <p>Current work -</p> <ol style="list-style-type: none">Building objects pypi.org libraryUsing OpenAI and DeepLearn.AI APIs with prompting and fact sheets <p>2.0 AI Agents for Enhanced Learning</p> <p>Focuses on enhancing educational methodologies using AI course agents. They create more interactive and personalized learning environment including</p> <ul style="list-style-type: none">• Lecture Content Transformation:<ul style="list-style-type: none">o AI agents convert lecture audio to text, building a class corpus for ai assistants• Synthesis and Interaction:<ul style="list-style-type: none">o Agents synthesize information and provide interactive learning experienceso Generate summaries and facilitating a cohesive understanding with materials	<p>▼</p> <p>>_0.0 Polysyllabics for authentic language exchange</p> <p>→ 1.0 Enhancing Language Authenticity</p> <ul style="list-style-type: none">↳ Schematic↳ Use polysyllabic and periphrastics in AI skilling↳ Goal:: logodaedaly library on pypi.org with APIs↳ perform syllabic assembly with topic relevance <p>→ 1.1 Methodology and tools</p> <ul style="list-style-type: none">↳ Design↳ List polysyllabic words by # of syllable trees↳ Transpose syllable trees -> ontological structures↳ Create:: (n x 3) by ontological and polysyllabic <p>→ 1.2 Entropic scoring mechanisms and refinement</p> <ul style="list-style-type: none">↳ Application and recursive learning↳ Evaluate for effectiveness and discourse scoring↳ Refinement with entropic scoring↳ how.TO:: increase clarity with noise scores <p>▼</p> <p>→ 2.0 AI Course Agents for Enhanced Learning</p> <ul style="list-style-type: none">↳ What↳ Convert lecture audio for class corpus text↳ Synthesize lecture notes and textbooks via APIs↳ Emailing lecture summaries and disparity indexes <p>→ 2.1 Interactive Learning Enhancement</p> <ul style="list-style-type: none">↳ AI Assistant agent↳ Feed media to AI for interactive student bots

Simply yet powerful generative ai tooling

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





backup schematics

