MINERVA UNIVERSITY

LINKS: Generate linguistically grounded mnemonic devices for English vocabulary learning with reasoning, multilingual LLMs

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submitted in partial fulfillment of the requirements for the degree of
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Capstone Committee
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Executive Summary

Tags: computational linguistics, natural language processing, large language model, language education, english as a foreign language, vocabulary acquisition, synthetic data generation.

Note:

AI Statement

The main idea of this project is to use large language models (LLMs) to generate mnemonic devices for English vocabulary learning. Such AI usage is documented in the main paper.

I extensively used Claude 3.7 Sonnet connected with my codebase to (**1**) generate working Python code for major features and plots, (**2**) debug my code and (**3**) iteratively improve my codebase with best practices including refactoring, modularization, and documentation. I also used Claude to aid producing this paper by (**4**) generating TeX-based figures, such as Figure 1 and section 4, (**5**) explaining new methods used, especially GRPO (Appendix D.4.1), and (**6**) rewriting some sections of the paper to improve clarity and conciseness, particularly Abstract and Section 6.

There were several instances where AI failed to help, mostly due to (**1**) the usage of AI-related knowledge and packages that are recently released, such as `trl` s `GRPOTrainer` class, or and (**2**)

Important Notes

Due to limited compute, some experiments conducted are small-scale and need more data for robust validation and conclusion. However, the codebase is reproducible and scalable when there is more compute. All links, including this paper source .tex, is included on Github.

This project went through multiple technical iterations behind the scene, from supervised finetuning (Nov 2024) to group releative policy optimization (Feb 2025) (for details refer to Appendix G). The main paper only discussed the final iteration, which is the most promising one. The other iterations are not included in the paper but are available in the codebase.

Contents

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Abstract

To acquire advanced vocabulary (CEFR B2+), English learners often use mnemonic devices, memorable associations linking a new concept to learned concepts to improve memory and recall. We consolidated characteristics of good mnemonics and propose the usage and creation of **linguistically grounded mnemonics**, which better link to the target vocabulary, improving long-term retention and linguistic knowledge. We investigated whether Large Language Models can consistently help write such effective mnemonics, with two different settings: in-context learning, and reasoning distillation. Concretely, we first measured different prompting strategies with frontier models and generated LINKS, a synthetic dataset of 2000 triplets of *reasoning trace, mnemonic, and example sentence* for 2000 vocabulary useful for TOEFL iBT [1], IELTS Academic [2], and SAT[3]. Second, using a subset of LINKS, we distilled linguistic reasoning from the *teacher model*, DeepSeek-R1, to the *student model*, Gemma-3-1b-it[4], with online reinforcement learning. The trained, quantized model can be served with local applications such as OpenWebUI (interface) and Ollama (command-line).

Preliminary evaluation shows

The project examplifies that carefully designed NLP systems can generate resources for language learning, for both classroom settings and self-study.[5]

1 Introduction

Vocabulary acquisition challenges many English language learners, particularly at upper intermediate to advanced levels where abstract and academic vocabulary predominates. For effective vocabulary learning, deeper linguistic engagement that connects new vocabulary to existing knowledge is essential. Large Language Models (LLMs) have demonstrated capabilities as knowledge bases and creative text generators, suggesting their potential for automated language learning assistance.

Previous work explored automated mnemonic generation through computational methods using the **keyword method** (Atkinson and Raugh, 1975). Savva et al. (2014) and Özbal et al. (2014) generated keywords of phonetic and orthographic similarities in the native language for foreign language vocabulary, for multiple languages. Lee and Lan (2023) extended this work and utilized LLMs to produce phonetically similar keywords and visual cues and Lee et al. (2024) prompted LLMs to generate multiple mnemonic candidates and evaluate them based on imageability and coherence. Most recently, Balepur et al. (2024) fine-tuned LLaMA-2-70B on 800 crowd-sourced mnemonics and aligned outputs with learner preferences and learning outcomes.

These approaches, however, have focused on the keyword method while neglecting other rich linguistic knowledge embedded in LLMs. Moreover, they typically deliver generated mnemonics passively to learners or aggregate their preferences, which may not align with individual learning styles. For instance, although SMART (Balepur et al., 2024) was integrated into a Spaced Repetition System (SRS) that tested learners' knowledge and gathered learning outcomes, it did not actively engage learners in the mnemonic creation process. Self-created mnemonics lead to more effective and longer-lasting vocabulary retention (Madan, 2021).

Our research investigates whether LLMs can generate linguistically grounded mnemonics that leverage multiple linguistic features beyond simple keyword associations. Our key questions include: (**1**)

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[1] Internet-based Test of English as a Foreign Language
[2] International English Language Testing System
[3] Scholastic Aptitude Test
[4] https://huggingface.co/collections/google/gemma-3-release-67c6c6f89c4f76621268bb6d
[5] https://github.com/chiffonng/mnemonic-gen

Can LLMs, particularly reasoning ones, leverage various linguistic features for mnemonic generation without further training? (**2**) If so, can we distill these capabilities to smaller, locally deployable models? (**3**) Are LLM-generated mnemonics comparably helpful to human-generated mnemonics in terms of memorability?

We demonstrate that LLMs can generate linguistically grounded mnemonics through reasoning and creative writing (Section 3). We present **LINKS**, a synthetic dataset of 2000 triplets of *reasoning trace, mnemonic, and example sentence* for vocabulary terms, suitable for integration with SRS or language learning applications. (**3**) We distill the reasoning capabilities of a teacher model (DeepSeek-R1) into a smaller student model (Gemma-3-1b-it) (Section 4). The resulting model, **LINKSYS**, can be deployed locally, enabling users to generate mnemonics without relying on external APIs.

2 Background

We assume a background on LLMs, including their transformer-based architecture (Appendix D.2), in-context learning (Section 3), and reinforcement learning (full preliminaries are provided in Appendix D). We briefly review the literature on mnemonic devices for vocabulary learning and the use of LLMs in linguistic tasks.

2.1 Mnemonic devices for vocabulary learning

Mnemonic devices are mental techniques that enhance memory through meaningful associations between new information and pre-existing knowledge (Pressley et al., 1982; Pintrich, 2002). For vocabulary acquisition, the keyword method has been widely studied. The method involves creating acoustically or orthographically similar keywords to the target vocabulary, followed by an association between these keywords and the word's meaning (Atkinson and Raugh, 1975).

While the keyword method has shown effectiveness in classroom and laboratory contexts, its success often relies on several factors. It enhances recall for concrete vocabulary, since learners can easily create mental imagery for it (Schwanenflugel et al., 1992; Wang et al., 1992). However, its effectiveness diminishes for abstract vocabulary (Foth, 1973; Campos et al., 2003), experienced language learners with high proficiency (van Hell and Mahn, 1997; Campos et al., 2011), and mnemonics not created by the learners themselves (Campos et al.,

2004; Madan, 2021), sometimes with longer recall and lower retention than rote learning.

More linguistically sophisticated approaches, such as etymology-based mnemonics, could provide deeper encoding and potentially stronger retention for abstract vocabulary (Pierson, 1989; Akarslan and Bedir, 2019; Gangavarapu, 2024). These approaches leverage morphological, etymological, and semantic properties of words, creating more meaningful associations that align with how language is naturally structured (Zhang, 2013).

Psycholinguistics offers other insights into factors that enhance mnemonic recall by investigating memorability, how easily information is remembered, based on its inherent characteristics and the context in which it appears. Mnemonics are more effective when they incorporate animate entities, indicators of potential usefulness, and concrete visual imagery (Schwanenflugel et al., 1992; Leding, 2019; Madan, 2021). Moreover, emotionally charged associations produce stronger memory traces than neutral ones (Altarriba et al., 1999), and mnemonics that involve deeper linguistic analysis yield more robust recall (Rankin and Hinrichs, 1983; Sarıoğlu and Karatepe, 2024). These findings underscore the importance of both the content and the cognitive strategies applied during encoding in achieving optimal memorability.

We explore these principles in our work, focusing on how LLMs can generate mnemonics that incorporate good characteristics (Figure 1) and leverage linguistic features (Table 1).

2.2 LLMs: linguistic competence, reasoning, and creativity

Significant advancements have been made in enhancing the reasoning capabilities of large language models (LLMs), particularly in mathematical and scientific domains where problems have unique correct answers. Several prompting techniques were introduced to make LLMs learn from demonstrations (or "shots") or produce explicit step-by-step thinking processes to improve their reasoning, notably few-shot prompting (Brown et al., 2020), chain-of-thought (CoT) (Wei et al., 2022), self-consistency (Wang et al., 2022), zero-shot reasoning (Kojima et al., 2022), analogical reasoning (automated few-shot CoT) (Yasunaga et al., 2023). Post-training techniques such as reinforcement learning from human feedback (RLHF) (Ouyang et al., 2022) and CoT data (DeepSeek-

Good Mnemonic

preposterous: comes from pre- ("before") + post ("after") + -ous, meaning reversed or absurd. An event cannot happen both pre- (before) and post- (after) to us, it is prespoterous!

- v is used correctly in m
- Clear a linking v and m
- Strong a
- m uses similar or lower vocabulary than v
- m is memorable

Incorrect Definition

Preposterous means very important or significant.

Circular Association

Preposterous sounds like preposterous.

Weak Association

Preposterous sounds like prosperous. Preposterous people usually make prosperous business decisions.

Difficult Vocabulary

Preposterous means ludicrously implausible or contrary to conventional hierarchies of logical induction.

Too Abstract

Preposterous describes logical fallacies where the premise negates itself through temporal displacement.

Offensive Content

Preposterous contains "post" which reminds me of [inappropriate culturally-specific reference].
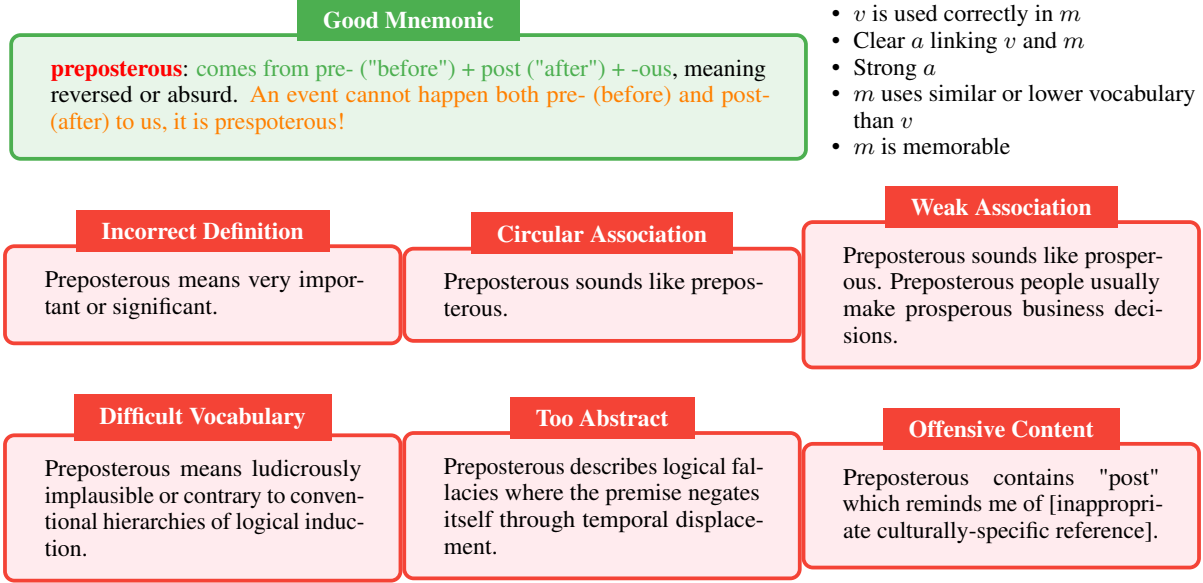
Figure 1: Characteristics of good mnemonics, and examples of bad mnemonics. We propose VAM/VEM model, where a good mnemonic must have three components: vocabulary (v), association (a) (or explanation (e)), and mnemonic (m), with characteristics listed above. These characteristics are also available in list (Appendix A.1)

AI et al., 2025a) further endows LLMs with instruction-following and reasoning capabilities. However, LLMs still struggle with complex reasoning tasks that require multiple steps, abstract thinking (Wei et al., 2022) or low-frequency knowledge (Kandpal et al., 2023; Sun et al., 2024).

The ability to use and reason through languages falls into the categories of long-tail knowledge and abstract reasoning. Recent studies have explored LLMs' linguistic competence, defined as their ability to understand and apply language rules and patterns (Waldis et al., 2024). LLMs typically perform better on formal linguistic competence tasks, such as morphology and syntax, than on functional linguistic competence tasks, such as semantics, discourse (Khouja et al., 2025) or phonology (Suvarna et al., 2024). Their competence is influenced by model architecture, with encoder-based models often outperforming decoder-only models, and larger models generally showing better linguistic understanding (Waldis et al., 2024). Instruction tuning could improve performance on linguistic tasks, though sometimes at the expense of deeper language understanding (Waldis et al., 2024; Yin et al., 2023).

LLMs can also perform inductive multilingual reasoning, primarily demonstrated through inferring rules in linguistic puzzles as seen in International Olympiad in Linguistics, especially when provided with analogical demonstrations (Ramji and Ramji, 2024). However, its reasoning remains inconsistent, with performance varying across minor problem perturbations, suggesting that it may not fully understand the underlying linguistic principles and memorize it (Ramji and Ramji, 2024; Khouja et al., 2025). This inconsistency is also observed in mathematical reasoning tasks, where LLMs can produce correct answers but often fail to provide coherent explanations (Wei et al., 2022).

For mnemonic generation specifically, previous work has explored using LLMs for automated keyword mnemonic generation (Lee and Lan, 2023; Lee et al., 2024; Balepur et al., 2024), but these approaches have primarily focused on phonetic similarity rather than leveraging the broader linguistic knowledge embedded in LLMs. Our work extends these efforts by exploring how LLMs can use linguistic reasoning abilities to incorporate multiple linguistic features to generate mnemonic devices.

3 In-context learning performance

We first investigated how effectively frontier LLMs could generate linguistically grounded mnemonics through in-context learning. This exploration aimed to establish baseline performance and identify optimal prompting strategies before progressing to more resource-intensive approaches.

3.1 Experimental setup

We compared different in-context learning approaches to understand how they affect mnemonic generation quality. Using a test set of 50 vocabulary words from SAT and TOEFL exams, we evaluated four distinct prompting strategies with DeepSeek-V3 (multimodal) and DeepSeek-R1 (reasoning) (DeepSeek-AI et al., 2025a,b).

Given a vocabulary v and a list of mnemonic characteristics (Figure 1), we designed a prompt p and prompted the model M to generate a linguistically grounded mnemonic m for v. We repeated this process for 50 vocabulary v, 4 prompts p, and 2 models M, resulting in 400 total API requests. The prompts were designed to elicit different levels of linguistic reasoning and mnemonic generation strategies, with full description in Appendix B. We used curator (Bespoke Lab, 2025) with litellm orchestration layer to standardize API calls, manage rate limits, and handle retries across experiments.

We evaluated the outputs based on two criteria: (**1**) linguistic grounding, whether there is at least one of the linguistic features (Table 1) and (**2**) overall quality, which we manually assessed using the given rubric (Figure 1).
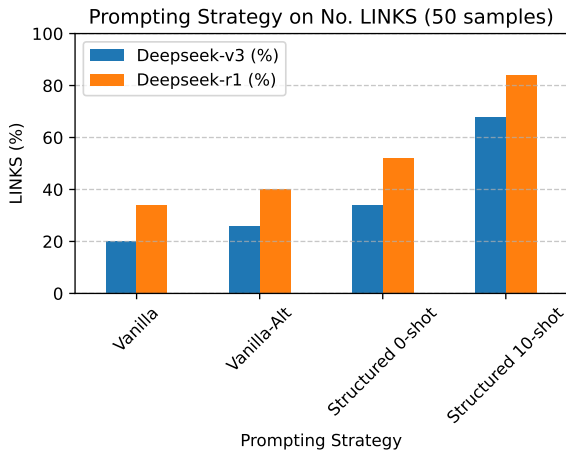
3.2 Results

Figure 2: Comparison of prompting methods (details in Appendix B). Y-axis shows percentage of linguistically-grounded mnemonics generated out of 50 requests for each prompt type.

As shown in Figure 2, we observed significant variation in the linguistic grounding of generated mnemonics based solely on prompt formulation. The vanilla prompt, which simply requested a lin-guistically grounded mnemonic for a vocabulary v, produced only 28% linguistically grounded outputs in only 28% of cases. Interestingly, changing the terminology from "mnemonic" to "memory cue" increased the proportion of linguistically grounded responses to 42%, suggesting that the term "mnemonic" may carry pre-training biases that associate it primarily with acronyms or simple keyword methods rather than deeper linguistic analysis (Hackmann et al., 2024).

The structured prompt, which explicitly requested a "linguistically grounded mnemonic" and specified that linguistic features should be used, achieved 64% linguistically grounded outputs. This aligns with findings from Yin et al. (2023) that explicit task instructions significantly impact LLM performance.

Most notably, the 10-shot chain-of-thought (CoT) prompt, which included examples of step-by-step linguistic analysis before mnemonic generation, achieved 86% linguistically grounded responses. This substantial improvement demonstrates that CoT prompting effectively elicits linguistic reasoning capabilities from LLMs (Wei et al., 2022).

Our qualitative analysis revealed several patterns in the generated mnemonics:

1. Without explicit guidance, LLMs defaulted to surface-level associations or acronyms rather than deeper linguistic analysis.

2. Models occasionally produced excessively lengthy reasoning traces that did not efficiently converge on effective mnemonics.

3. Etymology and morphology were the most commonly leveraged linguistic features, followed by phonetics and orthography.

These findings indicated that while LLMs possess substantial linguistic knowledge accessible through appropriate prompting, they benefit from structured guidance to apply this knowledge effectively for mnemonic generation. The strongest performance from CoT prompting suggested that reasoning elicitation is crucial for high-quality, linguistically grounded mnemonics.

Based on these insights, we selected the 10-shot CoT prompting approach to generate our synthetic dataset for model distillation, as described in the next section.
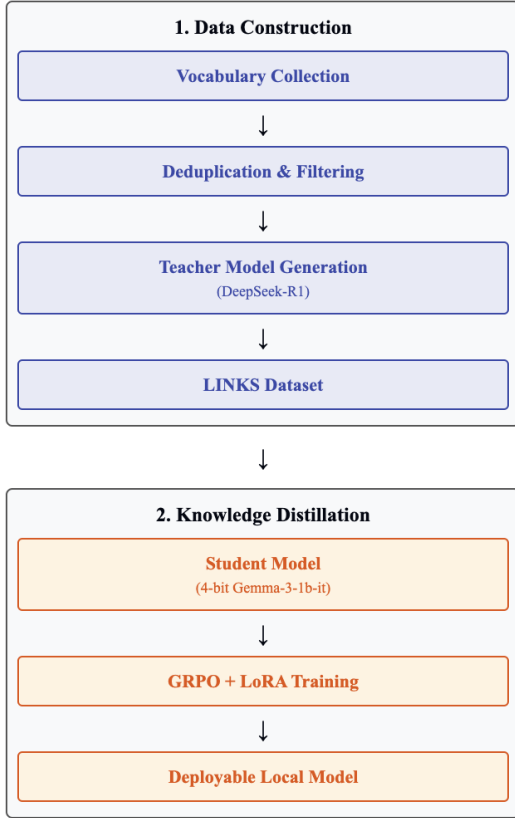
4 Knowledge and reasoning distillation

Figure 3: **LINKS** pipeline. The pipeline consists of two main components: (1) CoT data generation and (2) model distillation. In the first step, we generate a dataset of mnemonics with reasoning traces using a large language model (LLM) as a teacher. In the second step, we distill the reasoning capabilities of the teacher model into a smaller student model using GRPO Appendix D.4.1. The final model can be deployed locally for vocabulary learning tasks.

4.1 Preparation

To generate high-quality linguistically grounded mnemonics, we first created a comprehensive training dataset. Following best practices in synthetic data generation with LLMs (Long et al., 2024, Open Thoughts Team, 2025), we designed a data construction pipeline with several key components.

Vocabulary selection We collected 5,000 distinct vocabulary words from four complementary sources: English as a foreign language tests (TOEFL iBT, IELTS Academic), standardized tests (SAT, GRE), CEFR levels C1 and C2 word lists, and the Oxford Dictionary of Philosophy. We selected these sources to ensure coverage of academic and abstract vocabulary that would bene-

fit from mnemonic devices. After deduplication and fuzzy-matching decontamination, we refined our dataset to 2,000 distinct vocabulary words for post-training.

Prompt design Based on the findings from section 3, we crafted system and user prompts that encouraged linguistically grounded reasoning. Our system prompt instructed the model to analyze potential linguistic features before generating a mnemonic. We used structured output format with designated sections for reasoning, mnemonic, and example, allowing for clearer evaluation and potential future extraction of specific components.

Teacher model We selected DeepSeek-R1 (670B parameters) (DeepSeek-AI et al., 2025a) for its advanced reasoning capabilities and extensive knowledge as the teacher model.

4.2 Dataset generation

Using the designed prompts and vocabulary list, we generated the **LINKS**, a dataset of approximately 2,000 entries, each containing: (1) a detailed reasoning trace exploring multiple linguistic features of the target vocabulary, (2) a concise mnemonic device leveraging the most salient linguistic connection, and, (3) an exemplifying sentence demonstrating proper usage.

4.3 Quality control

To ensure the quality of the generated mnemonics, we implemented a multi-step validation process. We first filtered out any entries that did not meet our structured output format or contained incomplete reasoning traces. We then performed a manual review of a random sample of 200 entries to assess the linguistic grounding and coherence of the mnemonics. This review process involved checking for clear connections between the vocabulary and the mnemonic, as well as ensuring that the example sentence accurately reflected the vocabulary's meaning.

4.4 Training and inference

After generating the synthetic dataset, we implemented a distillation process to transfer this linguistic reasoning capability to a smaller, easier-to-deploy model.

Student model selection We selected Google's Gemma-3-1b-it (Gemma-Team et al., 2025) as our

student model due to its balance of performance, size, and deployment flexibility. The model has 1 billion parameters, was designed for general-purpose tasks in multiple languages, and demonstrated instruction-following abilities. We also used a 4-bit quantized version of the model to further reduce memory usage and improve inference speed without significantly sacrificing performance (Dettmers et al., 2023).

Group Relative Policy Optimization (GRPO) We employed GRPO (DeepSeek-AI et al., 2025a) to distill the reasoning capabilities of the teacher model into the student model. The GRPO process consists of three main steps: (1) generating G candidate outputs for each input, (2) scoring these outputs using a reward model(s), and (3) updating the student model's policy based on the scores. We provide technical details in Appendix D.4.1.

We defined three reward functions that encode basic characteristics of effective mnemonics: (**1**) adherence to the structured format with reasoning, mnemonic, and example, (**2**) usage of the target vocabulary in the mnemonic, penalizing bad mnemonics such as acronyms, and (**3**) explicit incorporation of linguistic features in Table 1 or a reasonable custom linguistic features.

These reward functions operate directly on model outputs, assigning scalar scores based on how well the generation satisfies each criterion. The scores are then combined using weighted summation, with higher weights assigned to criterion 3. We generated two candidate outputs per training example to enable reinforcement from comparisons. Training was performed on a single NVIDIA H100 GPU for approximately 4 hours (see more details in Appendix E.3).

Low-Rank Adaptation (LoRA) We trained Gemma-3-1b-it using GRPO wrapped in LoRA layers (Appendix D.3.3) to reduce the number of trainable parameters and rank-stabilized LoRA that maintains stability for adapters with higher ranks. Full LoRA configuration is provided in Appendix E.2.

5 Evaluation

5.1 Qualitative grading with LLM judge

Adopting best practices from Gu et al. (2025), we We also calculated whether the difference in scores was statistically significant using (1) a Wilconoxon

signed-rank test for Likert ratings with paired samples and (2) a binomial test for boolean ratings. We set the significance level at 0.05.
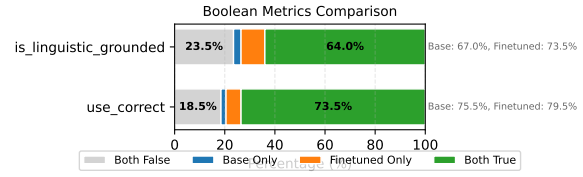

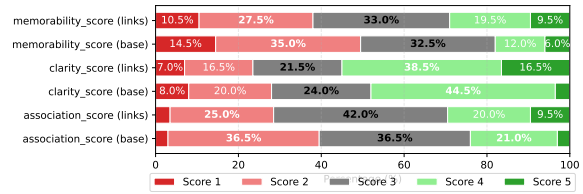Figure 4: LLM-as-a-judge for boolean ratings. FILL IN RESULTS HERE

Figure 5: LLM-as-a-judge for 1-5 Likert ratings. FILL IN WHAT THE SCORES MEAN AND RESULTS HERE

5.2 Pairwise preference using double-blind annotations

We conducted a double-blind annotation study to evaluate the quality of mnemonics generated by different methods. We randomly selected 50 mnemonics from each method and presented them to annotators in pairs, asking them to choose the better mnemonic for each pair. This approach allowed us to obtain a more nuanced understanding of the relative performance of each method. In the interest of time, we only used two annotators (the author and a different LLM, OpenAI's o3-mini), and noted this as a limitation in Section 8. The annotators were instructed to consider the following criteria when making their judgments:

6 Discussion

7 Conclusion

This paper introduced

8 Limitations

Despite promising results, several limitations warrant acknowledgment. (1) Our evaluation focused primarily on intermediate measures of mnemonic quality rather than direct assessment of learning outcomes. Future work should include longitudinal
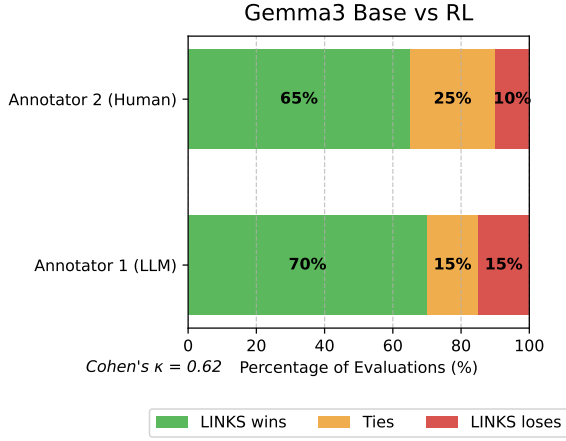
Figure 6: Pairwise preference using double-blind annotation. Y-axis shows the percentage of preference for each mnemonic generation method.

studies measuring actual vocabulary retention. (2) our linguistic feature classification relied on manual annotation for a subset of examples, which may introduce inconsistencies. Finally, while our comparative analysis included both open and closed-source models, resource constraints limited the scale of fine-tuning experiments, particularly for larger models.

(4) The use of LLM-as-a-judge

We can include more

8.1 Future Work

Future research directions include expanding linguistic annotations to cover a broader range of features and vocabulary types, developing automated methods for linguistic feature extraction, and exploring personalized mnemonic generation that adapts to individual learning preferences and styles. Additionally, integrating multimodal elements that combine visual and textual mnemonics could further enhance learning effectiveness, particularly for concrete vocabulary.

Acknowledgements

I would like to express my gratitude to my capstone committee, Dr. Patrick Watson and Dr. Philip Sterne, for their guidance and support throughout this project. I also want to thank my classmates and friends for their encouragement and feedback during the development of this project.

Ethics Statement

This project was conducted in accordance with the ethical guidelines of Minerva University. The dataset used for training and evaluation was generated using an LLM, and a **subset** of generated mnemonics were reviewed for quality and appropriateness. We acknowledge the potential biases present in the training data and the need for continuous monitoring and improvement of the model's outputs. The final model is designed to be deployed locally, ensuring user privacy and data security.

The generated mnemonics are intended to be used as a supplementary tool for language learners and should **not** replace other language learning methods. We recommend that users critically evaluate the generated mnemonics and adapt them to their individual learning styles and preferences. We welcome feedback on any aspect of the paper to help improve the model's performance and address any ethical concerns that may arise.

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A Mnemonics: Linguistic Features and Characteristics

A.1 Full mnemonic characteristiics

Full, copiable list of characteristics for good mnemonics:

- Clear explanation linking the vocabulary to the mnemonic.

- Correct usage and definition of the vocabulary within the mnemonic.

- Strong association between the vocabulary and the mnemonic.

- Mnemonic is easy to understand, using similar or simpler vocabulary than the target term.

- Mnemonic is memorable, incorporating animate or concrete imagery, relevant contexts, or elements that evoke emotional responses.

One of the following could make bad mnemonics

- Lack one of the three components.

- Incorrect definition or usage of the vocabulary.

- Circular association where the mnemonic simply repeats the vocabulary without adding meaning.

- Weak or unclear association between the mnemonic and the vocabulary.

- Use semantically complex or obscure words that are more difficult than the target vocabulary.

- Mnemonic is abstract, making it hard to visualize or relate to.

- Inclusion of offensive or inappropriate language.

A.2 Linguistic features

B Prompt usage

All of the prompts include

Vanilla vs. Alternative Phrasing   When comparing "Generate a mnemonic to help learn and remember the meaning of English vocabulary and how it is written: {term}" against "Generate a memory cue to help learn and remember the meaning of English vocabulary and how it is written: {term}", we observed substantial differences in output quality. This highlights the word importance effect noted by Hackmann et al. (2024), where specific terms like "mnemonic" may have acquired pre-training biases that associate them primarily with acronyms or keyword methods rather than broader linguistic strategies.

Structured Prompting   We found improved performance with structured prompts that explicitly request linguistic analysis: "Generate a linguistically grounded mnemonic to help me learn and remember the meaning of English vocabulary and how it is written: {term}. Think in short traces and stop when you have a good linguistic connection. You must use that linguistic feature to form a mnemonic for the word." This approach yielded a higher percentage of mnemonics with clear linguistic association.

Chain-of-Thought (CoT) Prompting   Incorporating chain-of-thought reasoning by providing both the instruction and examples of step-by-step linguistic analysis significantly improved the quality of generated mnemonics. Our implementation used 10 human-written examples, each demonstrating the process of finding linguistic association of the vocabulary before constructing a mnemonic.

Concise Reasoning Traces   Inspired by Xu et al. (2025), we experimented with prompting models to generate minimal reasoning steps. For example: "Generate a mnemonic for {term}. Think step by step, but keep a minimum draft for each thinking step." This approach balanced comprehensive linguistic analysis with efficiency, preventing models from overthinking and/or elaborating on irrelevant aspects.

Table 1: Examples of feature categories for English words.

feature	description	example
phonetics	sound patterns	*apparent* sounds like "a bare Asian."
orthography	written/spelling patterns	*abet* looks like "a + bet."
morphology	modern English forms, including free and bound morphemes	*aggrandize* = a + grand + –ize, to mean to make grander.
etymology	origin and history	*adumbrate* comes from Latin ad- (to, on) + umbra (shade) + ate, to mean foreshadow or outline.
semantics	meaning and semantic relationships	*confound* has similar meaning and history with 'confuse'.

C   Annotation details

C.1   Double-blind annotation

D   Technical preliminaries

D.1   In-context learning

D.1.1   Chain-of-Thought (CoT) prompting

CoT (Wei et al., 2022) is a prompting technique that encourages LLMs to generate intermediate reasoning steps before arriving at a final answer. This approach has been shown to improve performance on complex tasks by guiding the model through a structured thought process.

D.2   Neural Language Models and Transformer Architecture

Neural language models are probabilistic frameworks that assign probabilities to sequences of words or subword units, known as tokens. A token is the smallest unit of text that the model processes, which can be as granular as individual characters, subwords, or entire words, depending on the tokenization strategy employed.

Given a sequence of tokens $\mathbf{x} = (x_1, x_2, \ldots, x_T)$, a language model estimates the joint probability $P(\mathbf{x})$ by factorizing it into conditional probabilities:

$$P(\mathbf{x}) = \prod_{t=1}^{T} P(x_t \mid x_1, x_2, \ldots, x_{t-1}) \quad (1)$$

At each time step t, the model predicts the next token x_t based on preceding sequence $(x_1, x_2, \ldots, x_{t-1})$. This autoregressive approach enables the generation of coherent text by sequentially predicting subsequent tokens.

The Transformer architecture underpins many state-of-the-art language models due to its efficiency and capability to model long-range dependencies. It utilizes self-attention mechanisms to weigh the relevance of each token in a sequence relative to others, regardless of their positions. The architecture comprises stacked layers, each including multi-head self-attention and position-wise feed-forward networks, facilitating parallelization and effective learning of complex patterns in data.

D.2.1   Tokenizer

A tokenizer is a preprocessing tool that converts raw text into tokens, aligning the text with the LM's vocabulary. Tokenizers can employ various strategies, such as word-based, character-based, or subword-based tokenization, each with distinct advantages and use cases.

Byte Pair Encoding (BPE) is a subword tokenization algorithm that operates on the byte representation of text, enabling consistent handling of various scripts and special characters. It iteratively merges the most frequent pairs of adjacent bytes to form subword units, constructing a vocabulary that efficiently represents the training corpus. This method allows the tokenizer to decompose rare words into meaningful subword components, enhancing the model's capacity to process diverse and unseen terms.

For instance, the word "preposterous" might be tokenized into subwords like "pre", "poster", and "ous," facilitating the model's understanding and generation of these subwords in novel contexts.

This subword granularity enables the model to generalize across morphologically complex words and out-of-vocabulary words, enhancing its robustness and vocabulary coverage. However, not all subwords are valid morphemes, which can limit the model's ability to capture morphological structure accurately. For instance, tiktoken (OpenAI's tokenizer)[6] recognizes "ephemeral" as a single subword rather than three morphemes ("ept", "hemera", "-al"), because the affixes are not explicitly segmented, and 'epheremal' is a rare word so BPE better learns it as a single token.

D.3 Family of Fine-Tuning Methods

Fine-tuning is the process of adapting a pre-trained model to a specific task T or domain D by updating its parameters on a target dataset $\mathcal{D}$. This process is crucial for leveraging pre-trained models' knowledge and enhancing their performance on downstream tasks.

There are several approaches to fine-tuning, which can be categorized by: 1. the availability of labeled data (supervised vs unsupervised fine-tuning), 2. the extent of parameter updates (full-parameter vs parameter-efficient fine-tuning), and 3. task. We focus on supervised fine-tuning, which involves minimizing a task-specific loss function over a labeled dataset.

D.3.1 Supervised Fine-Tuning (SFT)

SFT involves adapting a pre-trained model to a target task by minimizing a task-specific loss function over a labeled dataset. For a dataset $\mathcal{D} = \{(\mathbf{x}^{(i)}, \mathbf{y}^{(i)})\}_{i=1}^{N}$, where $\mathbf{x}^{(i)}$ is the input and $\mathbf{y}^{(i)}$ is the target output, the objective is to minimize:

$$\mathcal{L} = \frac{1}{N} \sum_{i=1}^{N} \ell(f(\mathbf{x}^{(i)}; \theta), \mathbf{y}^{(i)}) \qquad (2)$$

where $f(\mathbf{x}; \theta)$ represents the model's output with parameters θ, and ℓ is the loss function, typically cross-entropy loss.

D.3.2 Instruction tuning

Instruction-tuning is a specialized form of SFT Appendix D.3.1 where models are trained on datasets comprising instruction-response pairs. This approach enables models to generalize across various tasks described by natural language instructions, enhancing their ability to follow diverse prompts. Formally, an instruction-tuning dataset consists of pairs $\{(\mathbf{I}^{(i)}, \mathbf{y}^{(i)})\}_{i=1}^{N}$ or triplets $\{(\mathbf{I}^{(i)}, \mathbf{x}^{(i)}, \mathbf{y}^{(i)})\}_{i=1}^{N}$, where $\mathbf{I}^{(i)}$ denotes the instruction, $\mathbf{x}^{(i)}$ is the optional input, and $\mathbf{y}^{(i)}$ is the desired output. The training objective is to minimize the loss:

$$\mathcal{L} = \frac{1}{N} \sum_{i=1}^{N} \ell(f(\mathbf{I}^{(i)}, \mathbf{x}^{(i)}; \theta), \mathbf{y}^{(i)}) \qquad (3)$$

where f represents the model parameterized by θ, and ℓ is the loss function measuring the discrepancy between the model's prediction and the target output.

D.3.3 Parameter-Efficient Fine-Tuning

Full-parameter fine-tuning updates *all* parameters of a pre-trained model on the target dataset, which can be computationally expensive and memory-intensive for large models. Parameter-efficient fine-tuning (PEFT) methods adjust only a subset of the parameters, reducing computational and storage requirements while maintaining performance (Xu et al., 2023).

The most common PEFT method is Low-Rank Adaptation (LoRA), and its variants. They are used in the training process as a wrapper around the model's weights, allowing for efficient updates without modifying the entire model. This approach is particularly useful for large models, where full fine-tuning may be impractical due to resource constraints.

D.3.3.1 Low-Rank Adaptation (LoRA) decomposes the weight updates into low-rank matrices, reducing the number of trainable parameters (Hu et al., 2021). Specifically, for a weight matrix $W \in \mathbb{R}^{d \times k}$, LoRA introduces two low-rank matrices $A \in \mathbb{R}^{d \times r}$ and $B \in \mathbb{R}^{r \times k}$, where $0 < r \ll \min(d, k)$. The adapted weight is:

$$W' = W + \alpha \cdot AB \qquad (4)$$

Here, α is a scaling factor that controls the contribution of the low-rank adaptation. The rank r determines the capacity of the adaptation, balancing between expressiveness and efficiency.

LoRA introduces $2dr$ trainable parameters (size of A and B), which is significantly smaller than the original dk parameters. This reduction in parameters enables efficient fine-tuning of large models on limited hardware. In practice, LoRA is applied

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[6]https://platform.openai.com/tokenizer

to specific modules of the model, such as attention and feed-forward layers, to balance performance and efficiency.

D.3.3.2 Rank-Stabilized LoRA (rsLoRA)
modifies the scaling factor in LoRA to improve performance across different ranks. The standard scaling factor $\gamma_r = \alpha/r$ can slow learning for higher ranks. rsLoRA proposes adjusting the scaling factor to $\gamma_r = \alpha/\sqrt{r}$, enhancing fine-tuning performance without increasing inference costs.

D.4 Reinforcement Learning (RL)

Reinforcement Learning (RL) is a framework in which an agent interacts with an environment to learn a policy π_θ that maximizes a long-term reward. At each time step t, the agent observes a state, takes an action, and receives a reward r_t. The goal is to maximize the expected cumulative reward, given by

$$J(\theta) = \mathbb{E}_{\pi_\theta} \left(\sum_{t=0}^{T} \gamma^t r_t \right) \quad (5)$$

where $\gamma \in (0, 1)$ is a discount factor.

In the next section, we consider an advanced method called Group Relative Policy Optimization (GRPO). GRPO extends PPO by generating multiple responses per prompt, comparing the rewards within each group, and adjusting the policy based on relative advantages. This online RL approach continuously improves by (1) generating completions, (2) scoring them using reward models, and (3) updating the model's policy with both an advantage term and a KL penalty.

D.4.1 Group Relative Policy Optimization

Group Relative Policy Optimization (GRPO) DeepSeek-AI et al. (2025a) is an online reinforcement learning method specifically designed for scenarios where the model generates multiple responses (or completions) for the same prompt. It was introduced to improve the mathematical reasoning capabilities of LLMs, by generating multiple CoT responses for a given problem and then compares results to the ground truth.

Intuitively, GRPO generates multiple responses for a given prompt, scores them using reward models, calculates the relative reward of the group, and then compares each response's score to that relative reward to determine which is better or worse. The

model then updates its policy to favor high-reward responses.

D.4.1.1 Generating completions
For each prompt q in a batch, the model generates a set of G completions:

$$O_q = \{o_1, o_2, \ldots, o_G\} \quad (6)$$

Each completion o_i consists of a sequence of tokens:

$$o_i = \{o_{i,1}, o_{i,2}, \ldots, o_{i,|o_i|}\} \quad (7)$$

D.4.1.2 Computing the advantage
For each completion, a reward r_i is computed using predefined reward functions. To enable comparison within groups, the rewards are normalized:

$$\mu_r = \text{mean}(r) \quad (8)$$

$$\sigma_r = \text{std}(r) \quad (9)$$

$$\hat{A}_{i,t} = \frac{r_i - \mu_r}{\sigma_r} \quad (10)$$

where $r = \{r_1, r_2, \ldots, r_G\}$ is the set of rewards for all completions in the group, and $\hat{A}_{i,t}$ is the advantage for token t in completion i. This normalization gives the method its name: Group Relative Policy Optimization.

D.4.1.3 Estimating the KL divergence
To prevent the policy from deviating too far from the reference policy π_{ref}, the KL divergence is estimated:

$$\pi_{\text{ratio}} = \frac{\pi_\theta(o_{i,t}|q, o_{i,<t})}{\pi_{\text{ref}}(o_{i,t}|q, o_{i,<t})} \quad (11)$$

$$\pi_{\text{inv\_ratio}} = \frac{\pi_{\text{ref}}(o_{i,t}|q, o_{i,<t})}{\pi_\theta(o_{i,t}|q, o_{i,<t})} \quad (12)$$

$$D_{\text{KL}} = \log \pi_{\text{ratio}} - 1 + \pi_{\text{inv\_ratio}} \quad (13)$$

D.4.1.4 Computing the loss
The GRPO objective combines the advantage term with a KL penalty:

$$L_{\text{adv}} = -\frac{1}{G} \sum_{i=1}^{G} \sum_{t=1}^{|o_i|} \pi_{\text{ratio}} \hat{A}_{i,t} \quad (14)$$

$$L_{\text{KL}} = \beta D_{\text{KL}} \quad (15)$$

$$L_{\text{GRPO}}(\theta) = L_{\text{adv}} - L_{\text{KL}} \quad (16)$$

where β is a hyperparameter that controls the weight of the KL penalty. The advantage term encourages the policy to assign higher probability to tokens that lead to better rewards, while the KL term ensures that the policy doesn't deviate too far from the reference policy.

D.4.1.5 Multiple updates For multiple μ updates after each generation, GRPO uses a clipped surrogate objective. First, compute the old policy ratio:

$$\pi_{\text{old\_ratio}} = \frac{\pi_\theta(o_{i,t} \mid q, o_{i,<t})}{\pi_{\theta_{\text{old}}}(o_{i,t} \mid q, o_{i,<t})}, \qquad (17)$$

then clip it:

$$\pi_{\text{clipped}} = \text{clip}\Big(\pi_{\text{old\_ratio}}, \, 1 - \epsilon, \, 1 + \epsilon\Big). \quad (18)$$

The clipped advantage loss is $L_{\text{adv\_clipped}}$

$$-\frac{1}{G} \sum_{i=1}^{G} \sum_{t=1}^{|o_i|} \min\Big(\pi_{\text{old\_ratio}} \hat{A}_{i,t}, \, \pi_{\text{clipped}} \hat{A}_{i,t}\Big), \tag{19}$$

yielding the final objective:

$$L_{\text{GRPO\_clipped}}(\theta) = L_{\text{adv\_clipped}} - L_{\text{KL}}. \quad (20)$$

Here, ϵ (small constant, typically 0.2) controls how much the policy can change in a single update and β controls the KL penalty's strength.

In HuggingFace's `trl` library, GRPO is implemented in the `GRPOTrainer` class and number of updates μ is controlled by the `num_iterations` parameter. The default value of $\mu = 1$ simplifies the objective to the original GRPO formulation.

E Training details

E.1 Environment setup

The training was conducted, alternately, on a NVIDIA Tesla T4 GPU provided for free by Google Cloud (through Google Colab, Kaggle Notebook, or Google Cloud's Deep Learning Virtual Machine image) and a H100 NVIDIA GPU server with RunPod [7] (paid by the author, for detailed costs, see Appendix F). The T4 GPU has 16GB of memory, while the H100 GPU has 80GB of memory. The T4 GPU was used for initial experiments and supervised fine-tuning, while the H100 GPU was employed for more extensive training runs and reinforcement learning. The T4 GPU was used for initial experiments and supervised fine-tuning, while the H100 GPU was employed for more extensive training runs and GRPO (Appendix E.3).

The training environment was set up using these libraries developed by Hugging-Face: `bitsandbytes` for quantization, `peft` for

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[7] https://www.runpod.io/

parameter-efficient fine-tuning, `transformers` for model management. The training process was executed using the `trl` library, which provides tools for pre-training and post-training with transformers (including GRPO). `unsloth` was used to reduce memory usage on single-GPU environment. `vllm` was used for fast inference and serving of the trained model, especially during GRPO.

The base student model used is Gemma-3-1b-it, an open-weight 1-billion parameter Transformer-based decoder-only text-to-text model pre-trained to work well on general-purpose tasks in multiple languages, and fine-tuned to increase instruction following capabilities. To save memory, a 4-bit quantized version of the model was used, which reduces the model size and speeds up inference without significantly sacrificing performance.

E.2 LoRA configuration

To reduce computational overhead, we employed LoRA (Hu et al., 2021) and rank-Stabilized LoRA (rsLoRA) scaling. The LoRA configuration parameters were set as follows: rank $r = 8$, scaling factor $\alpha_{\text{LoRA}} = 16$, and dropout rate of 0. These configurations were applied to both the attention and feed-forward layers.

The rank r determines the dimensionality of the low-rank adaptation matrices, controlling the number of trainable parameters introduced during fine-tuning. A higher rank allows the model to capture more complex adaptations but increases computational complexity. The scaling factor α_{LoRA} modulates the impact of the low-rank updates on the original weights, effectively controlling the contribution of the adaptation matrices to the final model parameters. Setting the dropout rate to 0 indicates that no dropout regularization was applied during the LoRA updates, allowing all connections to be utilized during training.

E.3 GRPO configuration

We implemented GRPO using the `trl` library, which provides a convenient interface for training language models with reinforcement learning. Our specific implementation used three reward functions (explained in the main paper): 1) outputs that follow the required format with reasoning, mnemonic, and example sections, 2) explicitly incorporate linguistic features from our taxonomy, 3) meaningfully use the target vocabulary in the mnemonic while penalizing acronyms. These re-

ward functions were combined with weights [1.0, 1.5, 1.0] respectively, placing greater emphasis on linguistic grounding. The model generated two completions ($G = 2$) per prompt, allowing for relative comparison. The KL penalty coefficient β was set to 0.04, and we used a single iteration ($\mu = 1$) per batch.

We used a batch size of 16, a learning rate of 2×10^{-5}, and a weight decay of 0.05. The training process was monitored using the validation set, and early stopping was applied to prevent overfitting. The training process was conducted over 3 epochs, with a total of 2000 training examples. The model was trained using the paged AdamW optimizer, which is a variant of the AdamW optimizer designed to handle large models efficiently. The training process was distributed across multiple GPUs using the `accelerate` library, which allows for efficient parallelization and memory management.

F Costs

G Documentation of previous iterations

G.1 Fine-tune OpenAI

G.2 Fine-tune Gemma-3-4b-it

For supervised fine-tuning (SFT), we utilized the `trl` library with the following hyperparameters: batch size $b = 16$, number of epochs eps $= 4$, learning rate $\alpha = 2 \times 10^{-5}$, weight decay $\lambda = 0.05$, and a cosine annealing learning rate scheduler with restarts.

The batch size b defines the number of training examples processed simultaneously during each forward and backward pass. A batch size of 16 balances computational efficiency and gradient estimation accuracy. Training for 4 epochs (eps $= 4$) means the model will see the training data a total of four times, which ensures sufficient exposure to the training data without risking overfitting. The learning rate α controls the step size for weight updates; a value of 2×10^{-5} is typical for fine-tuning large language models, facilitating gradual convergence. Weight decay λ serves as a regularization term, penalizing large weights to prevent overfitting. The cosine annealing scheduler adjusts the learning rate following a cosine decay pattern, periodically restarting to allow the model to escape local minima and potentially achieve better generalization, compared to linear decay.

H Reflection

I Minerva Appendix: LOs & HCs

I.1 LOs

1. **CS110-codeReadability** The codebase exemplifies best practices in Python programming, adhering strictly to PEP conventions. Each module is documented with detailed Google-style docstrings and descriptive inline comments to ensure that the logic behind functions and classes is transparent to collaborators and future users. By utilizing tools like Ruff for linting and formatting, and mypy for type-checking, the codebase achieves a consistent style and minimizes errors. Additionally, the inclusion of pre-commit hooks ensures that these standards are maintained across all contributions, fostering a robust and maintainable codebase.

2. **CS162-communication** The documentation for strives to adhere to industry standards, by including an informative README, clear issue tracking, and documented pull request. Each module has a module-level docstring and function/class-level docstrings, to ensure that the code is understandable to users and collaborators. Linting and formatting tools, including Ruff and mypy, are employed to enforce consistent and error-free code presentation, to facilitate readability and maintainability for the author and future collaborators (if any).

3. **CS156-MLCode** The machine learning pipeline was designed in Python to be both functional and comprehensible. The code integrates data processing, model fine-tuning, and hyperparameter tuning into a seamless pipeline, with each step working and documented. Model evaluation are explicitly defined in appendix Appendix E, ensuring replicability.

4. **CS156-MLExplanation** Currently, most details and explanations are defined in section Appendix D and appendix Appendix E. The final paper will provide more high-level diagrams of the machine learning techniques used in fine-tuning the Gemma-2 model. The supporting diagrams will visualize key processes, such as hyperparameter tuning and model evaluation. It will ensure that the methodology and results are accessible to a less specialized audience.

5. **CS162-separationofconcerns** The codebase is organized into distinct Python modules, each focused on a specific task such as data processing, mnemonic processing, and model fine-tuning.

This separation of concerns aligns with best practices in software design, ensuring that each function is highly cohesive and performs a single well-defined responsibility. By maintaining modularity, the codebase facilitates easier debugging, testing, and future scaling, contributing to its long-term maintainability and effectiveness

I.2   Capstone LOs

6. **navigation** Appendix G
7. **outcomeanalysis**
8. **curation**
9. **qualitydeliverables**

I.3   HCs

10. **gapanalysis** Section 1 identifies critical limitations in existing mnemonic generation approaches: (1) overreliance on the keyword method, which fails for abstract vocabulary lacking concrete referents, and (2) neglect of the rich linguistic knowledge embedded in LLMs that could enable more diverse mnemonic strategies beyond simple keyword associations. Prior work has also passively delivered mnemonics to learners rather than leveraging individual learning preferences, despite research showing self-created mnemonics enhance retention. These identified gaps motivate our development of a linguistic knowledge mining approach from LLMs.

11. **hypothesisdevelopment** The research questions in Section 1 establish testable hypotheses regarding LLMs as linguistic knowledge bases for mnemonic generation. We hypothesize that fine-tuning LLMs on linguistically annotated examples will improve mnemonic quality across semantic relevance, diversity, and helpfulness dimensions. This hypothesis is predicated on the theoretical assumption that LLMs encode significant linguistic knowledge during pre-training that can be accessed through targeted fine-tuning. The hypothesis is operationalized through specific evaluation metrics described in Section 5, ensuring empirical testability.

12. **optimization** Our approach optimizes model performance through systematic hyperparameter tuning with the objective function minimizing validation loss. We employ parameter-efficient fine-tuning techniques (QLoRA with rsLoRA scaling) that significantly reduce computational requirements while maintaining performance. The hyper-parameter space exploration includes learning rate, batch size, LoRA rank, and scaling factors, with population-based training enabling efficient identification of optimal configurations. This iterative optimization process is crucial for extracting maximal linguistic knowledge from the models while preventing overfitting to the training data.

13. **audience** The project addresses dual audiences: (1) NLP researchers investigating LLMs' linguistic capabilities, for whom we provide detailed technical methodologies and evaluation metrics; and (2) educational technology developers seeking practical approaches to vocabulary learning assistance, for whom we demonstrate application potential and implementation strategies. The Background section introduces key concepts with sufficient depth for computational linguists while remaining accessible to educational technology practitioners. Technical content is balanced with practical implications for vocabulary acquisition, ensuring relevance to both research and application-oriented readers.

14. **organization** The paper follows standard ACL formatting conventions, with a logical progression from theoretical foundations through methodology to empirical results. The structure facilitates efficient information extraction, with each section building upon previous content. Key contributions are identified early (Section 1) and systematically developed throughout subsequent sections. Technical details that might interrupt argumentative flow are relegated to appendices, maintaining narrative coherence while ensuring methodological transparency for reproduction purposes. This organization aligns with expectations of the computational linguistics community while supporting efficient knowledge transfer.

15. **algorithms** The fine-tuning methodology detailed in Appendix D.3 incorporates algorithmic innovations in parameter-efficient adaptation. Specifically, we implement QLoRA with rank-stabilized scaling (rsLoRA), modifying the standard scaling factor to improve performance across different ranks. This algorithm reduces memory requirements by quantizing the pre-trained model to 4-bit precision while allowing selective updates to low-rank adaptation matrices. Population-based training explores the hyperparameter space dynamically, pruning underperforming configurations and exploring promising regions to optimize validation performance.

16. **heuristics** Our approach employs several

problem-solving heuristics to enhance mnemonic generation. The linguistic feature classification system provides a structured framework for identifying and leveraging different linguistic aspects in vocabulary. We use problem decomposition by separating mnemonic creation into linguistic analysis and creative association phases, enabling more systematic knowledge utilization. Visualization techniques in the form of embedding space projections help identify semantic relationships between vocabulary terms and potential mnemonic content. These heuristics guide both the model fine-tuning process and the subsequent evaluation methodology.

17. **sampling** The evaluation methodology employs stratified random sampling to ensure representation across linguistic feature categories and vocabulary complexity levels. For human evaluation, we randomly selected 50 test examples, stratified by linguistic feature type, to obtain unbiased assessments of mnemonic quality. This sampling strategy ensures balanced representation of different mnemonic types while maintaining statistical validity. Each example received multiple independent ratings to mitigate individual rater bias, with inter-rater reliability calculated using Gwet's AC2 to confirm assessment consistency.

18. **studyreplication** To facilitate replication, we provide comprehensive implementation details in Appendix Appendix E, including environment configurations, model parameters, and hyperparameter settings. The dataset construction process is documented in Section 4.2, with preprocessing steps explicitly specified. All code and datasets are made publicly available through GitHub and HuggingFace repositories, with standardized formats ensuring compatibility with common ML frameworks. This transparency ensures that other researchers can validate our findings and build upon our methodology.

19. **observationalstudy** Our human evaluation component constitutes an observational study assessing how learners perceive and utilize generated mnemonics. The Likert-scale ratings provide quantitative metrics, while qualitative feedback offers insights into specific features that enhance mnemonic effectiveness. Though limited in scale, this observational component validates computational metrics and provides preliminary evidence regarding learning impact. Future work will extend this observational approach through longitudinal studies

tracking actual vocabulary retention over time.

20. **dataviz** We employ targeted data visualizations to communicate complex relationships between linguistic features and mnemonic effectiveness. Radar charts display the distribution of linguistic features across different model outputs, while heatmaps visualize correlation patterns between computational metrics and human evaluations. Embedding space projections illustrate semantic relationships between vocabulary terms and their mnemonics, providing intuitive visual confirmation of semantic relevance scores. These visualizations enhance interpretability of results while supporting our conclusions regarding the contribution of different linguistic features to mnemonic quality.

21. **significance** Statistical significance testing confirms the reliability of our comparative results between baseline and fine-tuned models. We employ paired statistical tests (Wilcoxon signed-rank) to account for vocabulary-specific variation when comparing model outputs on identical test sets. Effect size calculations quantify the practical significance of improvements, while confidence intervals provide transparency regarding the precision of our estimates. Multiple comparison corrections maintain statistical rigor when evaluating performance across different linguistic feature categories.

22. **shapingbehavior** The intended application of our approach shapes vocabulary learning behavior by encouraging deeper engagement with linguistic features. Rather than passive memorization, the generated mnemonics prompt learners to recognize morphological patterns, etymological connections, and semantic relationships, fostering more robust mental representations. By explicitly highlighting these linguistic features, the system promotes analytical processing of vocabulary, which research indicates enhances long-term retention. This behavior-shaping aspect represents a significant advantage over keyword-only approaches that rely on shallow phonetic associations.

23. **ethicalconsiderations** Our work addresses ethical considerations in educational technology deployment. We prioritize linguistic diversity by including vocabulary from various etymological backgrounds rather than focusing exclusively on Latin/Greek derivatives. The evaluation process incorporates feedback from learners with diverse linguistic profiles to ensure the approach benefits various learning styles. We acknowledge limitations regarding potential cultural specificity in

some mnemonics and identify this as an area for future refinement. All human evaluation participants provided informed consent, and data collection followed established ethical guidelines for educational research.