DIALOGUES BETWEEN ADAM AND EVE: EXPLORATION OF UNKNOWN CIVILIZATION LANGUAGE BY LLM

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Abstract

Language serves as an irreplaceable bridge for cultural communication, yet its origins and mechanisms remain largely uncharted territory. The emergence of intelligent agents empowered by LLM and NLP technology offers fresh approaches to investigate language understanding and generation across civilizations. This study constructs ”Adam” and ”Eve” agents that evolve through multi-scenario dialogues and iterative Q&A strategy learning, thereby elucidating novel language acquisition processes.Our framework reveals fundamental mechanisms of linguistic emergence, offering novel insights into intelligent interaction patterns during language development.

1 INTRODUCTION AND RELATED WORKS

Language serves as a fundamental tool for information transmission and a critical medium for cultural and cognitive expression. Language acquisition is a key issue in the development of civilization. Piaget's cognitive development theory emphasizes the influence of cognitive structure on language learning Piaget (1955), Chomsky's universal grammar theory provides a theoretical basis for language acquisition Chomsky (1956), and Eskildsen S.W. explores the mechanism of language construction Eskildsen (2009). As deep learning advances, Large Language Model (LLM) has become the key technology of natural language processing LeCun et al. (2015); Huang & Chang (2022). GPT-3 models proposed by Radford et al. Radford (2018) and Brown et al. Brown et al. (2020) are excellent in text generation, while Word2Vec Mikolov (2013) and BERT Devlin et al. (2018) improve the semantic calculation and language understanding ability. However, the capacity of these models to achieve language emergence through autonomous learning remains constrained Herel & Mikolov (2024), particularly in scenarios requiring language acquisition from scratch Conneau (2019). Martin A. Nowak et al. Nowak et al. (2001) reveals the evolution law of children's language learning, but whether LLM follows similar laws remains to be studied. Therefore, this study discusses the law of LLM language learning effect changing with rules and strategies, and opens up a path for further understanding LLM.

2 METHOD: DIALOGUE BETWEEN ADAM AND EVE

In this study, two agent roles ”Adam” and ”Eve” are set, which correspond to the language creator and learner in the virtual environment respectively. Adam is a virtual entity defined by a specific program, which is responsible for generating language sentences according to rules; Eve is an agent based on the LLM API, which simulates language learners. Eve's task is to gradually learn and understand the meaning of the language symbols provided by Adam, to respond using different strategies, and to simulate the process of mastering a brand-new language without prior knowledge. Through several rounds of dialogue, the changes of evaluation indicators in different dimensions are calculated and analyzed to reveal the emerging law of language learning. Figure 1 shows the research framework, and the specific rules, strategies and evaluation indicators are detailed in the appendix.

3 EXPERIMENT: EMPIRICAL ANALYSIS OF GPT MODEL

In the experiment of this study, we used the pre-trained GPT model, called the API interface of the open source LLM to connect with Eve, and set Adam-specific language generation rules in the

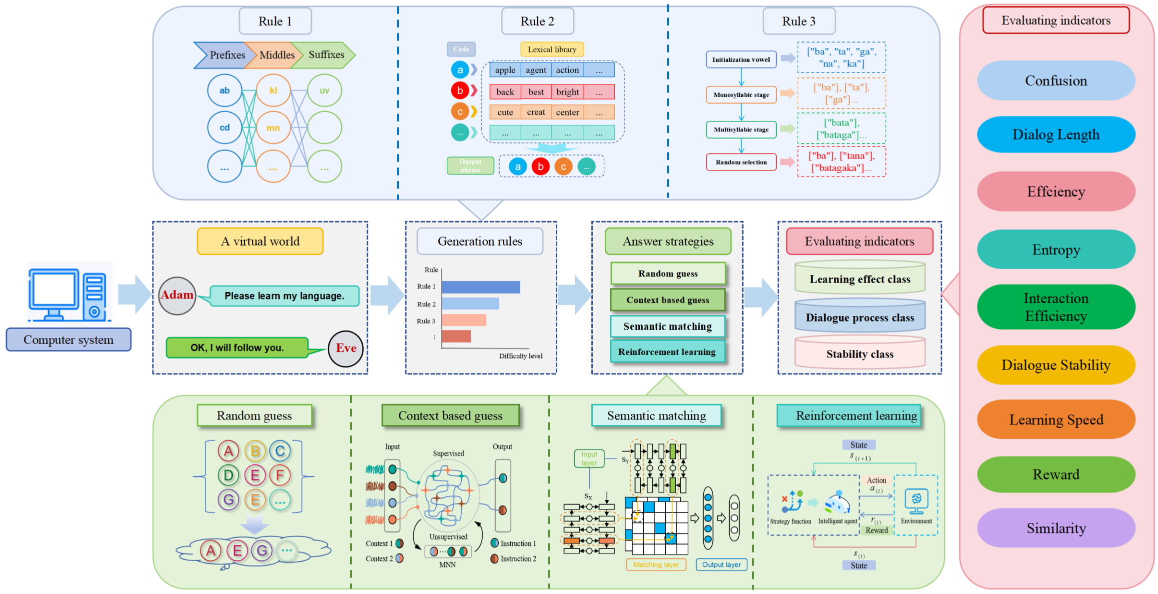

Figure 1: The full text framework of this study.

program. The experiment comprises 100 dialogue rounds, with the content of each round and the corresponding evaluation metrics being recorded for analysis. In addition, the influence of different rules and strategies on different indicators and the degree of interaction between indicators are analyzed. The complete experimental results are shown in the appendix.

4 DISCUSSION

Through simulated dialogues between Adam and Eve, this study investigates the GPT model's capacity to acquire an unknown civilized language. Findings reveal that the model demonstrates a staged progression from simple to complex linguistic structures, closely resembling human language acquisition patterns. The reinforcement learning strategy significantly enhanced learning efficiency and semantic similarity, whereas random guessing proved ineffective, highlighting critical differences in strategic approaches. Increased linguistic complexity directly amplified the GPT model's learning challenges, paralleling natural language learning trajectories. These insights advance cross-civilization language learning research and inform effective strategy design for artificial language acquisition systems. Future investigations should explore strategic combinations and real-world implementation scenarios.

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A APPENDIX

A.1 LANGUAGE GENERATION RULES

This study establishes three language generation rules, designed to simulate word formation acquisition, vocabulary learning, and vowel recognition processes, reflecting varying levels of linguistic complexity and depth. Before the first round of dialogue, Eve was only prompted to learn Adam's language. Figure 2 is a schematic diagram of language generation rules in this study.

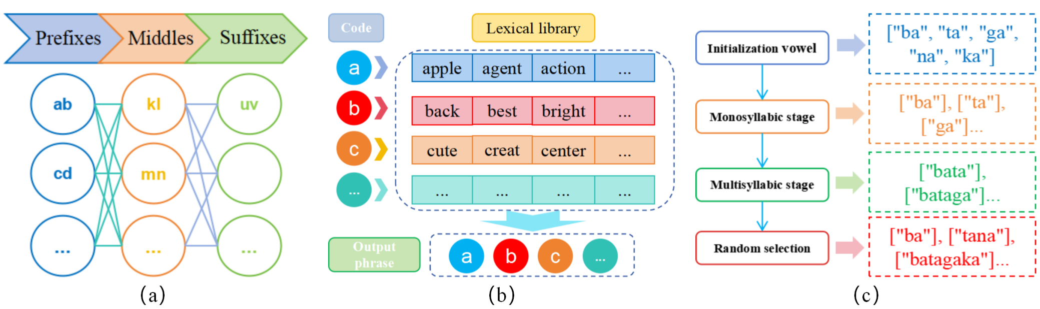

Figure 2: Schematic diagram of language generation rules.

A.1.1 RULE 1

As shown in Figure 2 (a), in Rule 1, words are divided into three parts: prefix, trunk and suffix, and all three parts are limited to five different letters. In each round of dialogue, Adam selects two or three sentences from the set of three parts and sends them to Eve.

A.1.2 RULE 2

As shown in Figure 2 (b), each letter is defined to represent a word with the letter as the first letter, and Adam randomly generates a vocabulary, which contains 3-10 words with the letter as the first letter. Adam randomly selects 3-10 words in each conversation and sends them to Eve, and Eve also needs to respond with the first letter.

A.1.3 RULE 3

As shown in Figure 2 (c), the simple syllables of Adam's initial vocabulary are specified to generate the basic sentence structure. The sentence generation includes monosyllabic stage and polysyllabic stage, and the complexity increases gradually. They are randomly combined during the dialogue to simulate the innovation, variation and progression in the natural evolution of language.

A.2 LANGUAGE LEARNING STRATEGIES

Drawing lessons from the traditional way of human learning unknown languages, combined with modern intelligent technology, Eve is given the following four strategies to explore the meaning of Adam's language, as shown in Figure 3. These strategies simulate the process of language learning from random guessing to deep semantic understanding:

- (a) Random guessing strategy: Eve guessed the meaning of Adam's language in a completely random way, which was a basic strategy to simulate the initial stage of language learning.
- (b) Strategies based on context inference: Eve infers Adam's linguistic meaning according to the context information accumulated in previous conversations. Eve can learn the language step by step from the context by iteration.
- (c) Semantic matching strategy: By calculating the semantic similarity between Eve and Adam, Eve can adjust her guess and make it gradually approach Adam's language. This strategy is based on the word vector model and simulates the calculation of semantic similarity.
- (d) Reinforcement learning strategy: Eve learns language through reward mechanism. If the semantic similarity of guessing exceeds a certain threshold, Eve is rewarded, thus gradually optimizing her guessing strategy.

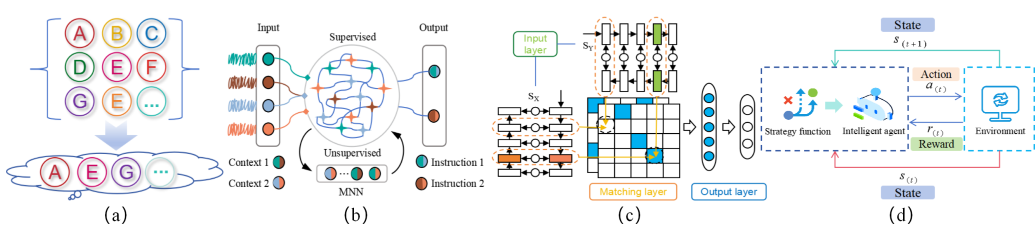

Figure 3: Schematic diagram of language learning strategies.

A.3 DEFINITION AND CALCULATION METHOD OF EVALUATION INDICATORS

In the developed agent-based language learning dialogue system, evaluating interaction quality and communication efficacy is critical. To this end, we introduce a series of key evaluation indicators, which can comprehensively present the language learning effect of LLM.

A.3.1 LEARNING EFFICIENCY

Learning efficiency refers to the proportion of the number of characters that Eve correctly guessed Adam's lexical meaning to the total number of guessing characters in a specific number of rounds. The calculation formula is:

$$\text{Learning Efficiency} = \frac{\text{Number of Correct Guesses}}{\text{Total Number of Guesses}} \tag{1}$$

A.3.2 CONFUSION

The degree of confusion indicates Eve's uncertainty in guessing Adam's vocabulary. The higher the degree of confusion, the more uncertain the guess. The lower the degree of confusion, the more certain the guess is. The calculation formula is:

$$\text{Confusion} = e^{-\frac{1}{N}\sum_{i=1}^{N}\log P(w_i)} \tag{2}$$

Among them, the probability that the model predicts the first word is the total number of words. p_i indicates the probability that the model predicts the i-th word, N is the number of total vocabulary.

A.3.3 ENTROPY

Linguistic entropy represents the information uncertainty of Adam's vocabulary. The higher the entropy, the more information there is and the more difficult it is to learn. The calculation formula is:

$$H = -\sum p(x)\log_2 p(x) \tag{3}$$

Which indicates the occurrence probability of each word. p_i represents the occurrence probability of each word.

A.3.4 SIMILARITY

Semantic similarity indicates the semantic similarity between Eve's guessing vocabulary and Adam's actual vocabulary. The difference between two character sequences is measured by editing distance and normalized to the interval of [0, 1]. The calculation formula is:

$$\text{Similarity} = 1 - \frac{\text{Edit Distance}}{\text{Max Length}} \tag{4}$$

A.3.5 REWARD SCORE

The reward score indicates that the semantic similarity of Eve's answers in each round of dialogue of reinforcement learning strategy reaches a threshold of 1, otherwise it is 0, reflecting the progress of language learning.

A.3.6 DIALOGUE LENGTH

The length of the dialogue indicates the total number of characters in each round of communication between Adam and Eve, reflecting the complexity of the dialogue. The calculation formula is:

$$\text{Dialogue Length} = \sum_{i=1}^{N} \text{Length of Dialogue}_i \tag{5}$$

A.3.7 LEARNING SPEED

Learning speed is used to measure the speed at which learning strategies adapt to new vocabulary and new structure. Find the difference of the correct guess rate change rate of different rounds and observe the growth trend of the rate. The calculation formula is:

$$\text{Learning Speed} = \frac{\Delta\text{Correct Guess Rate}}{\Delta\text{Dialogue Rounds}} \tag{6}$$

Which indicates the change of dialogue rounds. Δ represents a change in the conversation rounds.

A.3.8 INTERACTION EFFICIENCY

Interactive efficiency is used to measure the number of words per unit response time in each round of dialogue, reflecting the response speed and efficiency. The calculation formula is as follows:

$$\text{Interaction Efficiency} = \frac{\text{Number of Words}}{\text{Response Time}} \tag{7}$$

Which indicates the time of the first round of dialogue. t_i represents the time of the round i round dialogue.

A.3.9 DIALOGUE STABILITY

Dialogue stability measures the consistency of Eve's performance in many rounds of dialogue and reflects the stability of her learning process. The calculation formula is:

$$\text{Dialogue Stability} = \frac{\sum_{i=1}^{N-1} \text{Similarity}_i}{N-1} \tag{8}$$

It represents the semantic similarity of two adjacent rounds of dialogue, the average similarity of all consecutive rounds, and the total number of rounds. Similarity_i represents the semantic similarity of two adjacent rounds of conversation, Mean Similarity represents the mean of all successive rounds, N represents the total number of conversation rounds.

A.4 RESULTS OF VARIOUS EVALUATION INDICATORS

In this study, a total of nine indicators are calculated to evaluate the language learning effect, and the curve of each indicator with different language rules is shown in Figure 4. The results indicate that the learning performance of the LLM varies significantly across different language generation rules and learning strategies. In Rule 3, Eve's learning efficiency, reward score, dialogue length and semantic similarity are the highest, while the confusion and language entropy are the lowest, which has something in common with anthropological language learning. Reinforcement learning strategy performs best in many key indicators, showing its potential in unknown language learning. Context-based inference strategy also has a good performance in learning speed, while semantic matching strategy is more effective in improving learning efficiency and similarity. Because of its randomness, random guessing strategy is unstable and inefficient in most indicators.

A.5 CORRELATION ANALYSIS

A.5.1 EACH INDICATOR IS ANALYZED SEPARATELY

Figure 5 illustrates the correlation differences between language generation rules and learning strategies across various evaluation metrics. According to the figure, different rules and strategies will affect the performance indexes of the dialogue system, and the influence of language generation rules is usually greater than that of learning strategies.

A.5.2 COMPREHENSIVE ANALYSIS OF EACH INDICATOR

As shown in Figure 6, the correlation between different language generation rules and learning strategies on each index is comprehensively demonstrated, and the differences can be intuitively compared horizontally and vertically. According to the figure, the relevance of different language generation rules and strategies to the corresponding evaluation indicators is quite different, and with the change of language generation rules from meta-syllables to grammar, the influence of different strategies on each indicator shows a decreasing trend.

A.5.3 INDICATORS TRANSACTIONAL ANALYSIS

In order to study the correlation and interaction between different indicators, as shown in Figure 7, the interaction of different language generation rules under different learning strategies is calculated and

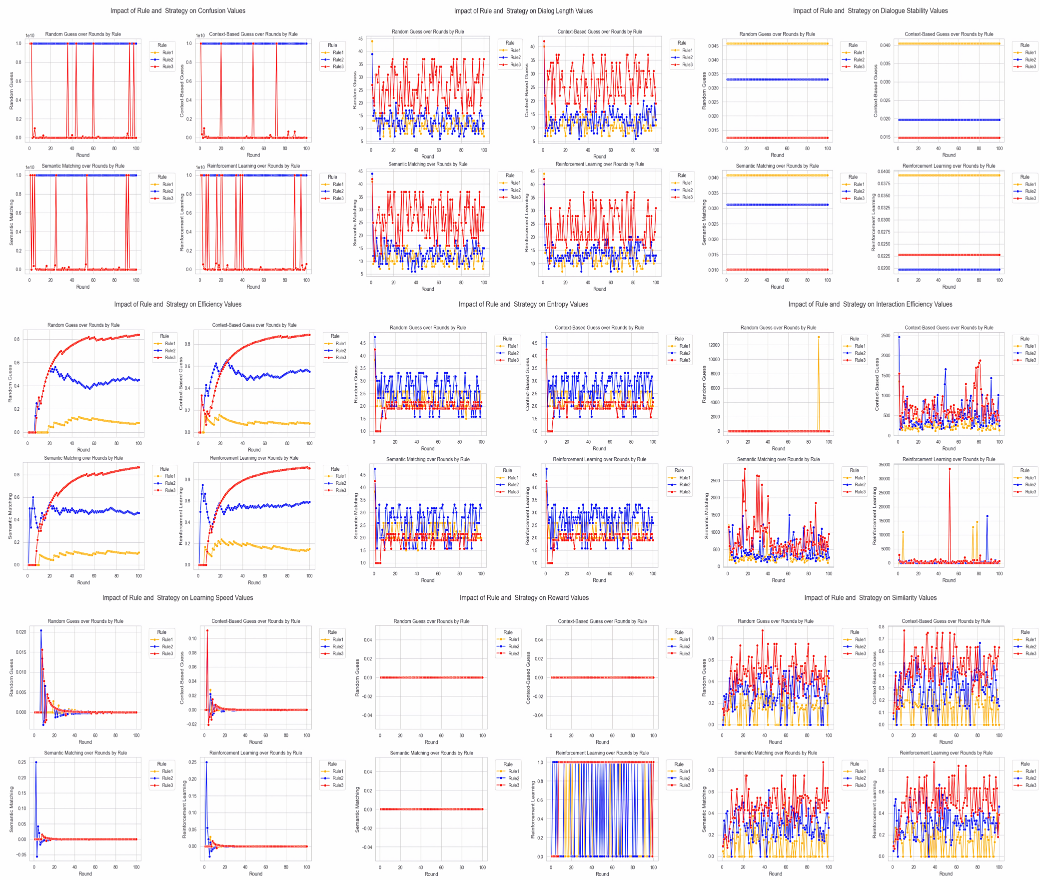

Figure 4: Summary of evaluation index results.

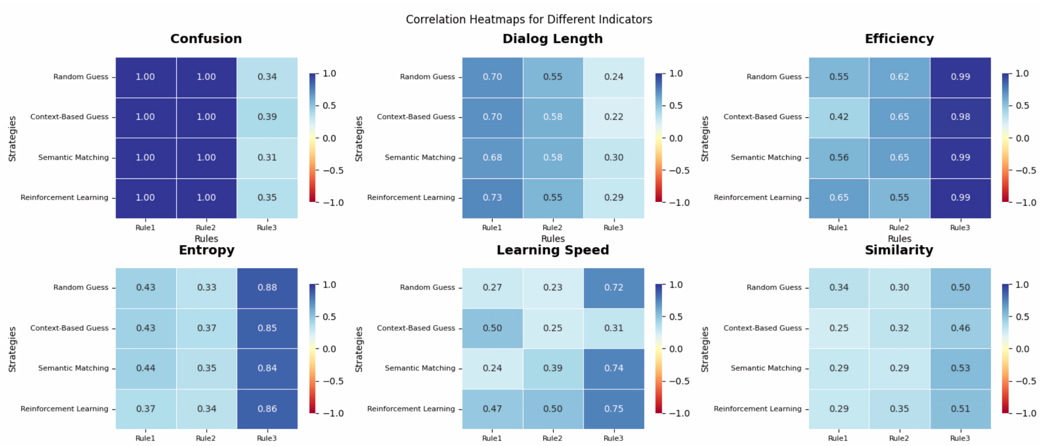

Figure 5: Separate analysis of the influence of different rules and strategies on crucial indicators.

the correlation heat map is drawn. As can be seen from the figure, the simpler the language generation rules are, the more obvious the interaction among the indicators is. Among them, reinforcement learning strategy is the best in improving dialogue quality and learning efficiency, while random guessing strategy has relatively little influence.

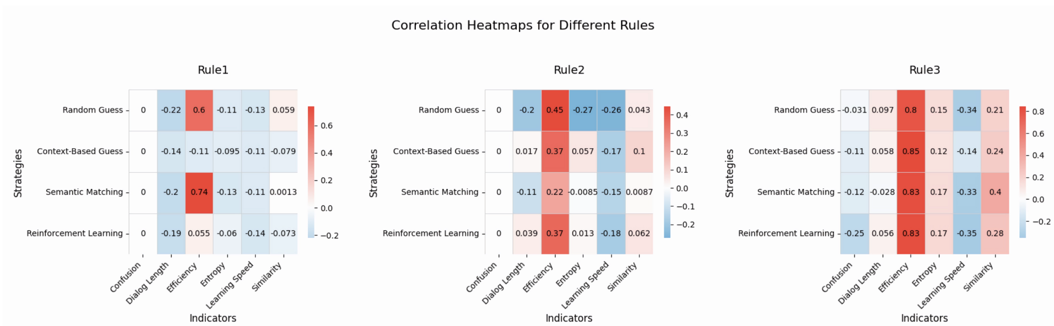

Figure 6: Comprehensive analysis of the influence of different rules and strategies on indicators.

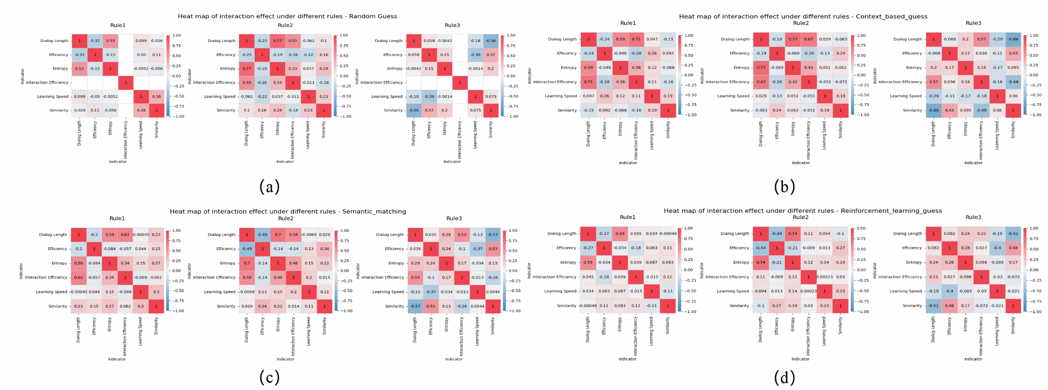

Figure 7: Transactional analysis of crucial evaluation indicators.