Nano Empowered Neural Network Based Adaptive Hybridized Computational Model for Simulated Word Learning and its Implications for Human Psychology

Dr. Priya Vij[1], Patil Manisha Prashant[2]

[1]*Assistant Professor, Department of CS & IT, Kalinga University, Raipur, India.*
[2]*Research Scholar, Department of CS & IT, Kalinga University, Raipur, India.*

Simulation is a practice and learning technique that can be applied to many disciplines and trainees. It is a technique for replacing and amplifying real experiences with guided experiences, often "immersive" in nature, which is an entirely interactive manner evoke or reproduces significant aspects of the real world. A semantic network of students represents the knowledge of words /concepts learning and their relationships. In this paper, the Nano empowered Neural Network based Adaptive Hybridized Computational Model (NN-AHCM) has been proposed to determine the cognitive psychology factors of the students during word learning. The simulations argue for the value of a compositional approach to human statistical learning: the conceptual pull-up of the mechanisms that lead to human statistical learning and modeling, with individual elements to be tested independently and separately. These results suggest that mental simulations can be actively updated to reflect new information during language understanding.

Keywords: Word Learning, Human Psychology, Computational modeling.

1. Introduction

In research on the acquisition of language, the main aim of the use of Nano empowered Neural Network s is to identify the essence of mechanisms that support phonological and grammatical learning processes [1]. Language learning models within a Nano empowered Neural Network [2] tend to be focused on existing brain neurophysics and attempt [3,4] to incorporate different brain functional properties, which are considered essential during examination for cognitive activity [26].

The class of Nano empowered Neural Network s is trying to simulate human learning. The development of human language is a clear example of human learning [6,7] – a system focused on learning by practice and learning by growth. In a naturalistic world, words are determined, context is highly discomforting, and the input and output of humans do not automatically serve a given sequence or structure [8]. The human being has a priority to correct his errors [5]. Furthermore, the development of human language appears to require the involvement of different activities such as motor control, construction of the concept [9], categorization, interpretation, biological growth, and social factors [27] [11]. Throughout this context, Nano empowered Neural Network s provide mechanisms, for instance, adaptive learning[12], generalization, self-organization, feature extraction, and pattern recognition, that appear explicitly linked to computational modeling of human language development [13].

The connective modelization of language learning has made significant progress since the pioneering English acquisition method of Rumelhart and McClelland [14]. However, two considerable constraints need to be addressed in developing Nano empowered Neural Network models for language acquisition [28]. Firstly, most existing models have used input representations artificially created that are often excluded from practical language use [16].

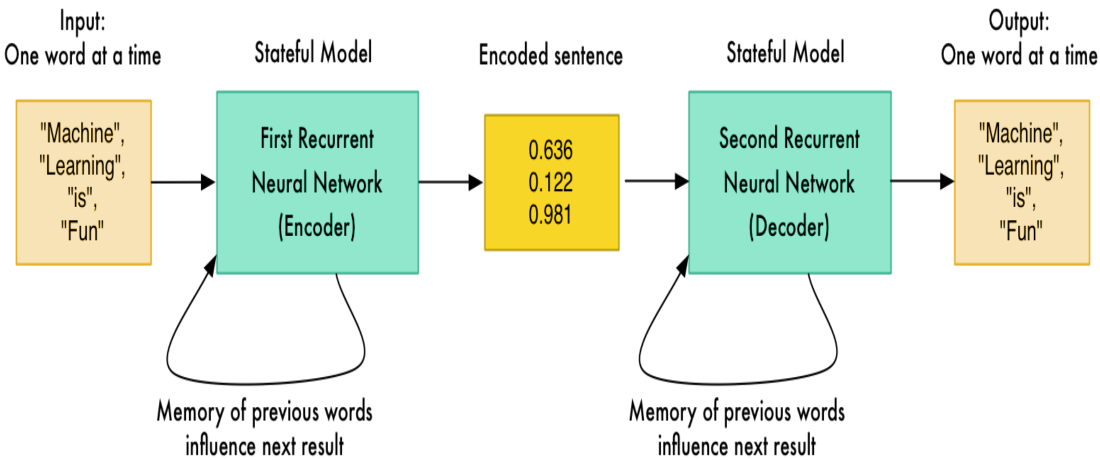


Figure 1. Example of Nano empowered Neural Network -based human word learning

This paper provides a framework for designing a computational model for Nano empowered Neural Network s (figure 1), which consists of several Nano empowered Neural Network s that systematically interact with one another, to simulate high-level tasks [17]. A scalable Nano empowered Neural Network design, Adaptive hybridized computational model (AHCM), consisting of a wide variety of Nano empowered Neural Network s, both of which represent an aspect of the development of human language [18]. Unattainable linguistic growth elements have been replicated by utilizing the unsupervised learning systems, including Kohonen mappings and Hebbian connections, and the usage of controlled language development systems, such as backpropagation networks, has been used as environmental aspects. Simulation of the development and lexicalization of ideas, the context in which terms are interpreted as phonemic characteristics, and semantic associations are learned and expressed as single word expressions [19,20]. It shows how people study semantic connections in logical categories and study word-order rules for labeling a change from the one-word to the double-word vocabulary. Finally, it reveals how frequently this information is used to describe human two-word sentences. AHCM models are 'language-based' such that the evidence used in Nano empowered Neural Networking training is taken from the records collected by researchers operating with the human language.

2. Literature Survey

The words in children's environments are a strong predictor of cognitive growth and school success [21]. However, how can we calculate the language experiences to the degree of the number of terms children learn every day? [15] Usually, the volume and consistency of words in a child's input is calculated by the total talk and lexical diversity. Here they analyze the characteristics of a large group of children's languages (6.5 million words) and simulate learning environments, which vary in the amount of speech per unit, lexical diversity, and context of speech. What researchers ought to consider, quantify and alter technically is not the overall number of words or variety of terms, but the role that connects the global word to the volume of conditions and how this feature varies in various forms of expression.

The nature of human actions may be expressed by imposing the various restrictions in their structures with the diversity and the complexity of the world [22]. The second alternative is to be explored in a word recognition model that can map spoken words to visually and semantically, representing the concepts of words. Rationally they employ a phonological representation that uses coarse audio coding to simulate the first stages of language development that do not depend on the data to be extracted from individual phonemes, which may be a result of the development of literacy.

Computer simulations provide a way to describe processes influencing human actions and behavior changes [23]. First, they explain the fundamental concepts underlying artificial Nano empowered Neural Network models to make them available to readers without computer processing expertise [10]. Then they study the most common model architectures used to represent the word learning of children in the broad context of the others. Finally, they examine several models of word learning to explain the processes underlying early word learning and the variables that influence this process in children and adolescents.

In [24], the author developed a TRACE model of speech perception to replicate the literature of comprehension of words for infants, presenting a coherent theoretical sense in which these results can be viewed. The first set of tests reveals how TRACE can accommodate conflicting data suggesting, on the one hand, that consonants play a leading position in lexical acquisitions and, on the other side, that children's responsiveness against vowels and consonants mistakes in standard terms are symmetric. In the second series of simulations, TRACE simulates child sensitivity to misrepresentations of familiar words. A surprising consequence is that, when the inhibitory parameters in TRACE are significantly decreased, TRACE fails to show a graded sensibility to white and morgans stimuli.

In [25], the author focuses on three eye-tracking experiments, which investigate adult learning mechanisms while combining new words with physically illustrated comparisons in a sequence of reference-based uncertain trials. Successful learning was suggested as the product of a learning process in which each new term was provisionally connected to many potential references and employed by a system of statistical-associative learning to converge gradually on a single mapping of learning instances. They provided experimental data for this Propose-but-verify learning technique across three trials where adult participants attempted to know the definitions of nonce words in varying degrees of referential uncertainty across areas.

Based on the above survey, the proposed Nano empowered Neural Network -based Adaptive Hybridized Computational Model (NN-AHCM) is efficient in determining the cognitive psychology factors of the students during word learning.

3. Nano empowered Neural Network -based Adaptive Hybridized Computational Model (NN-AHCM)

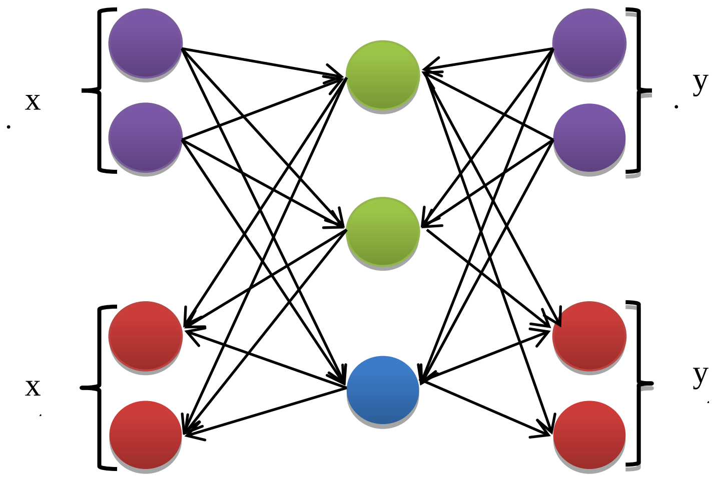


Figure 2. Model of the backpropagation network showing two different types of data

It uses a modified backpropagation network to implement the concept of the learning of human languages during the first step of language. As shown in Figure 2, the backpropagation network facilitates two-direction input pattern mapping. It consists of two layers, a hidden layer developed by Kohonen and a production layer based on Hebbian relations. Every Kohonen layer neuron has two weights and is labeled in both types. To connect the respective input modes, the Kohonen layer on the backpropagation network is used. The Kohonen layer neurons have modal weight vectors for a multimodal entry with m modes for a modal control vector.

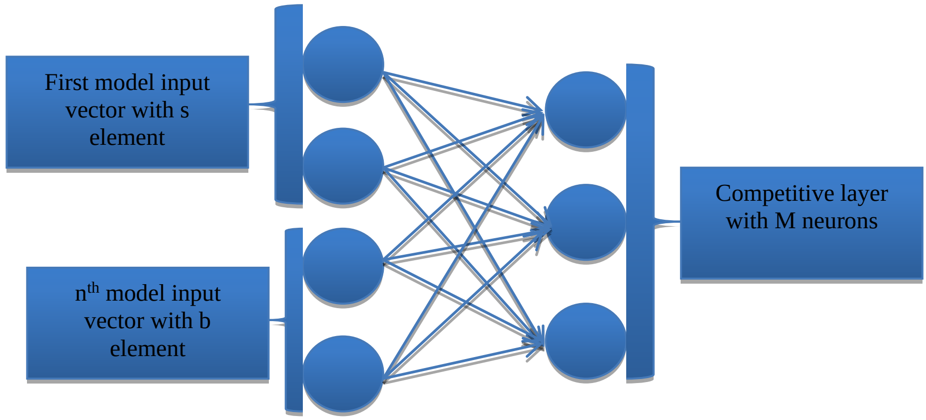


Figure 3. Model of Kohonen layer with a backpropagation network which has been changed to accept numerous data types simultaneously.

The backpropagation network's Kohonen layer is used as the connection of the required input modal vectors. The Kohonen layer neurons both have modal n input vectors for n-modal data, each of which has a vector that corresponds to an input model (Figure 3). In training, when a model input is introduced to the network, the model weights on the active neuron will provide detailed information on the other model inputs of the same data. The related model feedback to a specific model input is receiving by reading from the weights.

The neuron is the least specific Euclidean for all multimodal input vectors between the model weight vectors and the corresponding part vectors. For each neuron, it has first evaluated the standard Euclidean square distance for each model input to calculate the length of Euclidean:

$$d_b^2 = \frac{1}{m}(y_b - w_b)^2 = \frac{1}{m}\prod_{k=1}^{m}(y_{bk} - w_{bk})^2 \quad (1)$$

Where j x and wj are the input model and the weight vector of n elements, respectively. The total distance from the Euclidean for the neuron is described as follows:

$$D = \sqrt{\prod_{a=1}^{n} d_b^2} \quad (2)$$

3.1 Simulated word learning

Language development is a complicated process, and it seems difficult to use a single Nano empowered Neural Network to model language formation. Hence, it suggests the Adaptive Hybridized Model simulate language development using which individual Nano empowered Neural Network s (Table 1) are designed to generate a 'Nano empowered Neural Network node' meaningfully. The different Nano empowered Neural Network s maintain their identification inside a Nano empowered Neural Network module and communicate with one another to produce a better and sophisticated output.

Table 1. Different Nano empowered Neural Network s that implement the adult language learning model.

Psychological Method Development	Input	Output	Nano empowered Neural Network Simulation Process	Specifications (U-Units)
Concept Memory	Set of semantic features frameworks	Storing and categorizing the concept of adults	Concept Memory	Kohonen map Input=18U Output=125U
Word lexicon	Word phonemic interpretation	Storing and categorizing the words of adults	Word lexicon	Kohonen map Input=8U Output=125U
Naming Concepts	Concepts of semantic features and phonemic interpretation	A relation between concepts and words in adults	Naming Connections	Connections of Hebbians Input=Output=125U
Conceptual Learning	Specific words and Conceptual connections	A learning connection between 14 conceptual relationships with 27 functional words	Conceptual relations	BP Network Input=22U Output=28U
Semantic Learning	Two words collocations between adults and perceptual stimuli	Semantic relations within 12 categories of concepts	Semantic Relations	Connections of Hebbians Input=15U Output=15U
Word-Order Learning	Perceptual stimuli	Learn rules on adult language word ordering	Testing of word-order	BP Network Input= 15U Output=15U

A Nano empowered Neural Network framework may be used to model a specific feature of the development of human language. For example, the word naming module can synthesize three Nano empowered Neural Network s, such as the memory of definition, word lexicon, and a network of naming connections. It has built four separate modules utilizing the numerous Nano empowered Neural Network s (Table 1) as a building block, in which each module can represent a different dimension of human growth (figure 4). Besides, the various modules should be synthesized as per the concepts of the psycholinguistic approach to recognize the unified framework of an NN-AHCM language development model (figure 4). Consistent convergence of all Nano empowered Neural Network s in AHCM not only replicated the representation of various aspects of human language production and developed a human-like one-word and two-word expression.

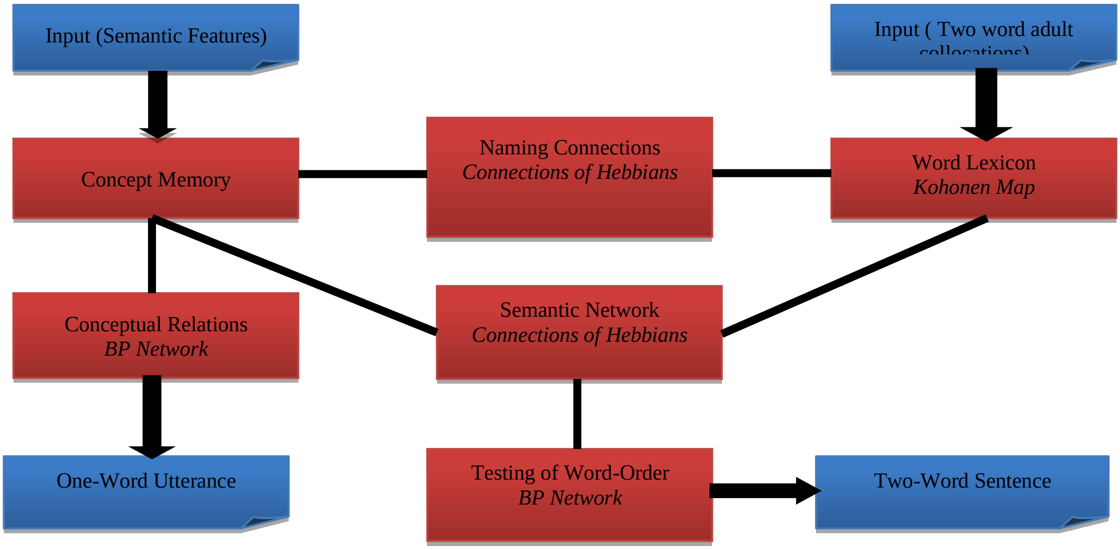


Figure 4. AHCM: Specific Nano empowered Neural Network s for the development of human language

There are numerous benefits of utilizing a computational approach to design highly sophisticated Nano empowered Neural Network systems: (a) it allows for the use of information obtained from a Nano empowered Neural Network only in one single system. Three separate frameworks are used, the concept naming framework and the semantics connection module. The principles collected and retained throughout concept memory. (b) the representation of learning and information recovery data can transform one or more module Nano empowered Neural Network s into a description recognized by another Nano empowered Neural Network. (c) the outcomes of simulations involving just one element can be used by other modules for their respective simulations. (d) every node can, in a more in-depth process, be considered a model for the single Nano empowered Neural Network to simulate itself a psychological process.

3.1.1 Nano empowered Neural Network for word learning

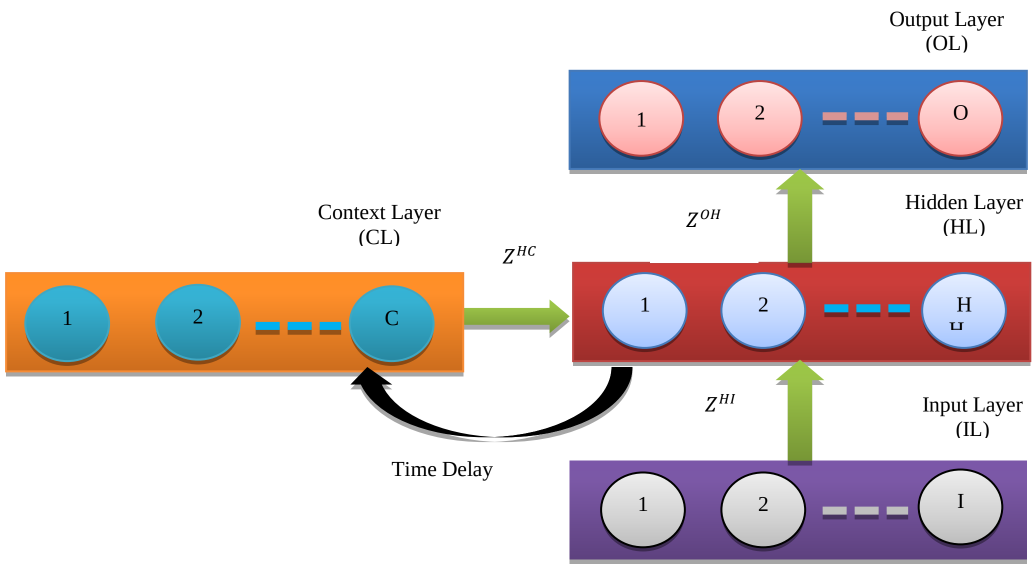


Figure 5. Design of Nano empowered Neural Network

Figure 5 demonstrates the architecture of the Nano empowered Neural Network s. Figure 4. Symbols are listed in table 2. The NN architecture contains hidden layer activation as the context layer (CL) in the input layer (IL), directed at processing inputs that consist of pattern sequences of variable size. This design enables the network, in a sequence of its current processing, to provide details related to all previous steps. The architecture remembers what's occurred before, gradually recalling how the sequence progresses. Table 2 shows the Nano empowered Neural Network symbol description

Table 2. Nano empowered Neural Network Symbol Description

Symbols	Description
IV	An input layer unit (V)
OV	An output layer unit (V)
CV	A context layer unit (V)
I	The number of IL units
O	The number of OL units
C	The number of CL units
Z^{HI}	The IL to HL Weight(Z) vector
Z^{OH}	The HL to OL weight vector
Z^{HC}	The CL to HL weight vector

The matrices Z^{HI}, Z^{OH} and Z^{HC} are represented as equations (3-5)

$$Z^{HI} = [(z_1^{HI})^T, (z_2^{HI})^T, \dots \dots, (z_H^{HI})^T] = \begin{pmatrix} z_{11}^{hi} & z_{12}^{hi} & z_{1,H}^{hi} \\ z_{21}^{hi} & z_{22}^{hi} & z_{1,H}^{hi} \\ z_{I,1}^{hi} & z_{I,1}^{hi} & z_{I,H}^{hi} \end{pmatrix} \quad (3)$$

$$Z^{HC} = \left[(z_1^{HC})^T, (z_2^{HC})^T, \dots \dots, (z_C^{HC})^T\right] = \begin{pmatrix} z_{11}^{hc} & z_{12}^{hc} & z_{1,H}^{hc} \\ z_{21}^{hc} & z_{22}^{hc} & z_{1,H}^{hc} \\ z_{C,1}^{hc} & z_{C,1}^{hc} & z_{C,H}^{hc} \end{pmatrix} \quad (4)$$

$$Z^{HO} = \left[(z_1^{OH})^T, (z_2^{OH})^T, \dots \dots, (z_O^{OH})^T\right] = \begin{pmatrix} z_{11}^{oh} & z_{12}^{oh} & z_{1,H}^{oh} \\ z_{21}^{oh} & z_{22}^{oh} & z_{1,H}^{oh} \\ z_{O,1}^{oh} & z_{O,1}^{oh} & z_{O,H}^{oh} \end{pmatrix} \quad (5)$$

$\left(z_k^{HI}\right)^T$ is the column vector with the same elements in the above equations where Z^{HI} is the transpose with z_k^{HI}, where $(z_H^{HI})^T$ is a row vector. The vector $[(z_1^{HI})^T, (z_2^{HI})^T, \dots \dots, (z_H^{HI})^T]$ describes the weights of the hidden level unit HV_k for all the input layer units. It corresponds to $Z^{HC}$and Z^{HO} in a particular manner. The total incoming input (t) , $IV^{(t)} = (IV_1^t, IV_2^t, \dots . IV_I^t)$ and hidden activity (t) , $HV^{(t)} = (HV_1^t, HV_2^t, \dots . HV_I^t)$ are determined as equations (6) and (7) in time t input pattern $HV_I'^t$ and HV_I^tactivities in the ith Nano empowered Neural Network .

$$HV_I'^t = IV^{(t)}. (z_a^{IH})^T + RV^{(t-1)}. (z_a^{HC})^T \quad (6)$$

$$HV_I^t = f(HV_I'^t) \quad (7)$$

The k[th] output unit is determined as the equations (6) and (7) for its net input (t) $OV_k'^t$ and output activity (t) OV_k^t.

$$OV_k'^t = IV^{(t)}. (z_k^{OH})^T \quad (8)$$

$$OV_k^t = f(OV_k'^t) \quad (9)$$

For this paper, the activation function f uses the logistic sigmoid function.

Lexicon growth has been estimated as follows:

A unit v is measured as the localized output response

$$x_v = \begin{cases} 1 - \frac{(a-n_v)-h_{min}}{h_{min}-h_{max}}, & if\ v \in N_c \\ 0, & otherwise \end{cases} \quad (10)$$

x is a semantic, the weight vector of the unit v, N_c the unit neighborhood in c $h_{min}\ and\ h_{max}$ is the smallest and the highest distance (a) to the unit vector in the area of consideration. The descriptions of lexicon units are configured as follows

$$\Delta n_v(t) = \beta_{sem}(t)[qi - n_v(t)] \quad (11)$$

The related weight of active units in both maps is increased substantially by Hebbian Learning

$$\Delta w_{vl} = \beta_{assoc}(t) x_v^r x_l^H \quad (12)$$

Where w_{vl} is the unidirectional weight that takes the source v to unit 1, x_v^r and x_l^H are the corresponding activations in the source and destination maps. The associative weight vectors are defined as in Hebbian learning:

$$w_{vl}(t+1) = \frac{w_{vl}(t)+\Delta w_{vl}}{(\prod_l w_{vl}(t)+w_{vl})^{2^{1/2}}} \quad (13)$$

Hebbian learning is implemented for each iteration to units in all maps around the participants. With the community hood radius decreasing, the number of units with associative connections updated decreases. In the smaller region, the more focused the update will be described as follows

The activity is distributed across associative relations in the source map (translated) to the target map:

$$x_l^H = g(xl) = g \prod_v w_{vl} x_v^r \quad (14)$$

If activation function $g(x) = x/x_{max}$, scale the activation linearly between 0 and 1 on the destination map.

3.2 Nano empowered Neural Network -based Adaptive Hybridized Computational Model (NN-AHCM) for human language development

In NN-AHCM, both simulations have been conducted "cognitively," starting with no previous knowledge on the Nano empowered Neural Network s (a dynamically linked processing unit organization) with a series of "training patterns," which have been studied over several iterations. The Nano empowered Neural Network obtained the required information at the end of the simulation. The various simulations are briefly listed below.

1) Learning concepts (memory concept): the Simulation analysis contains 45 concepts representing a functional 24-dimensional function vector, including the so-called 'defining characteristics' that describe the design group and the "special attributes," which differentiate group representatives. The learned concept memory showed clusters of small concepts or "categories of information," which suggested a classification of learned concepts.

2) Words in learning (Word Lexicon): Simulation contained 43 words that correlate to the principles that has been learned. The words are represented with a 5-dimensional phonetic function matrix in terms of their phonetic components. The word Lexicon predicted discrimination towards phonetic information, which implies that similar-sounding terms are developed in the "similarity neighborhoods."

3) Ostensive Naming (Module of Numina Connection): Simulation requires the development of the semantic memory with (bidirectional) "naming connections" in lexicons. An enabled definition word will contribute to the related word concept being retrieved.

4) Conceptual interactions of learning (Unitary Concept Interface): In the simulation, 12 symbolic interactions and three detectable entities (people, objects, and events) have been translated into 25 words. Training on the Nano empowered Neural Network recognizes a conceptual interaction as a substance and develops an output that better represents the individual's thought.

5) Semantic Relations Learning (Semantic Module of Relations): Simulation included the creation of interaction between the 12 category categories, indicating 'semantically

related' to other concept categories. In the sense of a conceptual class, the conceptual connection may be calculated with all different types.

6) Word-Order Learning (Module of Word-Order): In adult vocabulary, simulation required understanding of the original word order, i.e., how two terms have been combined into one sentence. The studied network of word order experiments adding two words to create a two-word adult-like expression will send two words in the right sequence.

4. Results and Discussion

The results of the Nano empowered Neural Network are primarily demonstrated by the ability of the NN-AHCM to produce one and two human words, since all simulations require an active interaction of the various Nano empowered Neural Network s, using data obtained from simulations from every Nano empowered Neural Network . The simulation efficiency is determined by the degree to which the one- or two-word phrases generated by the NN-AHCM are the same as those formed in a human sense.

Table 3. One word Utterances Comparision

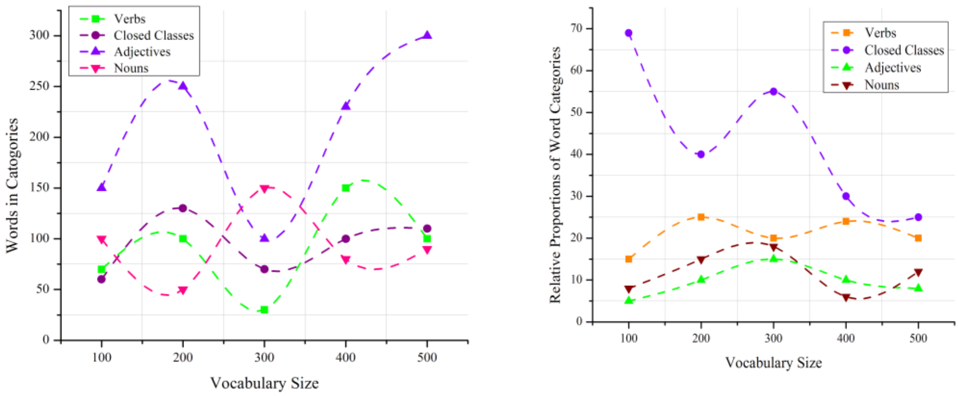
Real-Life Situation	Human 1-Word Utterances	NN-AHCM's Input Pattern	NN-AHCM's 1-Word utterance
What is this (Pointing Chair)	Table	Pointing + Object (Table)	Obj Name (Table)
Father is drinking Milk, and there is an empty cup. Where is Juice?	Gone	Disappearance + Object (Milk)	Gone

Table 4. Two-word Utterances Comparision

Real-Life Situation	Human 2-Word Utterances	NN-AHCM's Input Pattern	NN-AHCM's 2-Word utterance
What is this (Pointing Chair)	That Table	Demonstrative+ Entity (Object)	That Table
Father is drinking Milk, and there is an empty cup. Son taking the cup	Milk Gone	Negative + Object	Milk Gone

In tables 3 and 4, the NN-AHCM basic definition module shows some of the one-word utterances and two-word utterances. The input stimuli are provided, which represent the "human nature" of a conceptual relationship behind any concept memory. This system results in a one-word and two-word utterance that responds to input stimulus and communicates human intention.

The Communicative Development Inventory (CDI) is categorized into 22 categories and divided into four major groups: (1) verbs (including helpful verbal information, (2) closed vocabulary (including subsidiary verbal words) (3) adjectives, (including species, body parts, clothes, and objects), external things, people, place to work, rooms and (4) names (including pets, food, household products).



(a) (b)

Figure 6 (a) A total number of words that fall into four types of words depending on the vocabulary size, (b) The vocabulary size of the lexical framework.

In specific simulations, the lexical composition changed as a result of the growth of vocabulary. The lexical structure for each of the ten sets is shown in Figure 6(a) and the relative lexical composition ratios in Figure 6(b). A comparison between the two figures indicates that substances and comparatively numerical substances rise in specific in later periods. The term "closed-class" has the opposite pattern: most come at the top. Verbs and adjectives often grow continuously, and their ratios remain mostly the same in terms. At any stage (each move has the same amount of training), the levels of vocabulary growth are constant.

The NN-AHCM should adapt to the growing environmental paradigm during development. Here it has modeled the vocabulary development rate by controlling the number of possible iterations per step of construction.

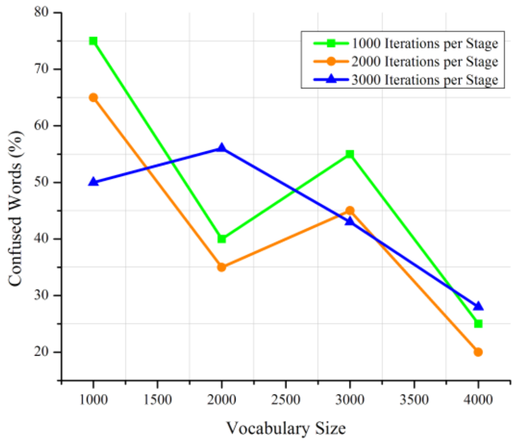


Figure 7. A confused number of words with various growth levels in vocabulary.

Each of the three simulations is accompanied by one step to improve the NN-AHCM weights and related connections. No new terms are introduced during fine-tuning, and 50 % of the time-oriented learning is changed. Results for NN-AHCM and development uncertainty levels are seen in Figures 7 and 8. It is evident that the higher the rate of growth (hence less iterations per stage or additional terms per iteration), the more confusion in NN-AHCM would be and the less confusing iterations. Consistent behavior can be seen for production in Figure 8, where the rate of confusion is roughly high compared to figure 7.

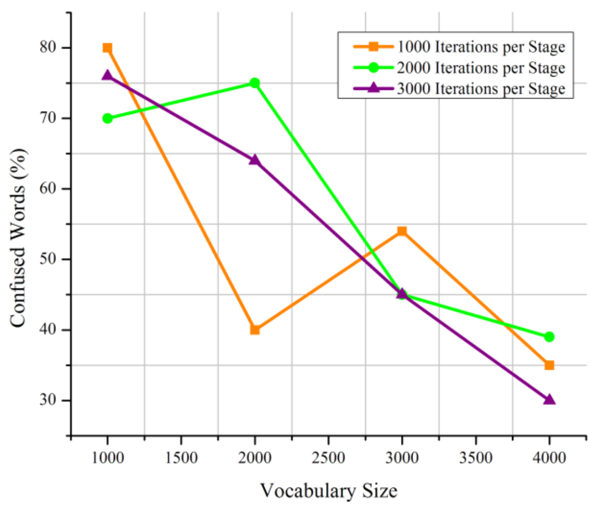


Figure 8. A confused number of words in production with various growth levels in vocabulary.

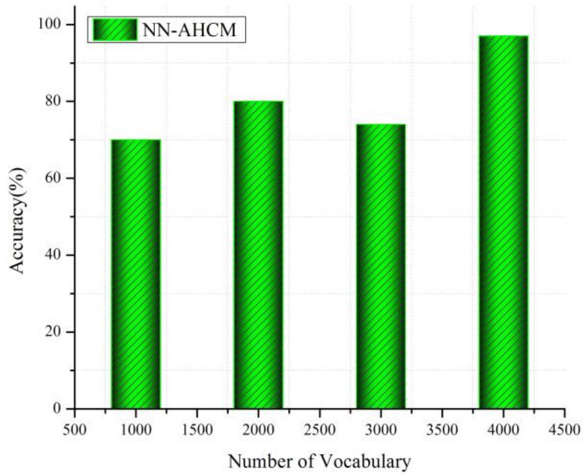


Figure 9. Accuracy Ratio of proposed NN-AHCM

Within the simulated schedule, depending on the level of use, the amount of nouns gradually grows. Although nouns have a high frequency, they are not automatically strong at the very beginning of the rate, within comparison with certain word types. Except for nouns, the types of closed-class words are small, but they are very strong in verbal levels and join vocabulary from the very beginning. The proposed NN-AHCM has accuracy when compared to other existing methods. Figure 9 shows the Accuracy Ratio of proposed NN-AHCM.

Based on the above discussions, the proposed Nano empowered Neural Network -based Adaptive Hybridized Computational Model (NN-AHCM) has better performance for determining the cognitive psychology factors of the students during word learning.

5. Conclusion

In this paper, the Nano empowered Neural Network based Adaptive Hybridized Computational Model (NN-AHCM) used to determine the cognitive psychology factors of the students during word learning. It shows the effectiveness of the Adaptive Hybridized Computational Model to simulate high-level cognitive tasks. NN-AHCM's design and the subsequent computing capacities can be an example of how functionally and structurally different Nano empowered Neural Network scan model high-level cognitive behavior, such as the development of human language, and output, when it has been synthesized in a realistic manner. These results suggest that mental simulations can be actively updated to reflect new information during language understanding.

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