Research Article

Dynamic Model of Language Propagation in English Translation Based on Differential Equations

Wenping Wei [ID]

School of Primary Education, Xianyang Vocational and Technical College, Xianyang 712000, China

Correspondence should be addressed to Wenping Wei; wwx2876@dlsud.edu.ph

English is the most widely used language in the world, and at the same time, English translation is becoming increasingly important. However, the traditional English translation model still has some problems, such as poor translation effect, repeated translation, translation solidification, and translation limitations caused by regional language differences in the application process of language communication. Differential equations refer to relational expressions containing unknown functions and their derivatives. Solving differential equations is to find unknown functions. Differential equations are a branch of mathematics developed along with calculus. In order to solve the problem, this paper puts forward the use of differential equation thinking research English translation language propagation dynamic model, the differential equation combines the neural network language model (NNLM) to form the language dynamic propagation using the differential equation and NNLM model algorithm of the dynamic model for the actual translation effect test (the database includes more than 3,000 indexed, abstract journals and newspapers, including nearly 3,000 full-text journals. The database covers topics, such as international business, economics, economic management, finance, accounting, labor and personnel, and banking. It is suitable for professionals in economics, business administration, financial banking, labor, and personnel management, etc.), and analyze the average code length and the first word hit rate of general language model (GLM), NNLM model, and domain model in the dynamic model in different fields. Then its statistics the overall recall rate and accuracy rate of the dynamic model. The results show that the average code length of the NNLM model is relatively shorter at 2.2 bits. The first word hit rate is higher than the other two models. The first word hit rate of the NNLM model is 85% under non-professional phrases, while 90% under professional phrases. The overall accuracy of the English translation of the dynamic model of language propagation in this paper is 86.37%, and the recall rate is 79.67. It shows that the dynamic model of language propagation combined with neural network and differential equation has a good translation effect and is feasible.

1. Introduction

In the context of global integration, English translation is essential in the world for any person. In language input, GLM is usually obtained by statistic on the comprehensive corpus of various fields, and a language model under the average condition is obtained, but it does not have the characteristics of the domain. The corpus of the domain language model comes from relevant texts in a specific domain, which can reflect certain domain characteristics. However, due to the large number of fields and the limited storage space, it is impossible to collect large-scale corpora for each field one by one. Meanwhile, it is not possible to

collect large-scale corpus in advance in some emerging fields. Due to differences in education, experience, living environment, etc., each person inevitably has differences in language usage habits. The user language model can record the user's historical input information and adjust it dynamically to adapt to different users, which can solve the problem of differences. Through continuously recording the user's input information, the domain features of the model can be enhanced. In statistical machine translation, translation prediction considers not only the aligned source words themselves, but also their source contextual information. Learning contextual representations is a promising approach to improve translation results, especially through

neural networks. Most existing methods process context words sequentially, ignoring source long distance dependencies. Language is interpreted more as a social semiotics than a system of the human mind. In many phenomena, in nature and engineering, these formulations are generalized as clear solutions to differential equations. Partial differential equation problems can also be transformed into differential equation problems to approximate solutions. Therefore, the numerical solution of differential equations is the basic content of numerical analysis of differential equations.

In order to solve the shortcomings of traditional language models, many scholars have studied some other English translation models. Among them, Kim et al. proposed an automatic translation method for phrase-based statistical machine translation. Probabilistic translation models consisting of phrases could be learned from large parallel corpora with larger language models. The method showed statistically significant improvements compared with entropy-based pruning on real-world translation tasks for English-Spanish and English-French pairs. It was up to 50% more efficient and trims 12% more on average to show the same translation quality [1]. Chen et al. proposed a novel neural approach for translation prediction based on source-dependent contextual representations. The proposed model was not only able to encode source long-range dependencies, but also capture functional similarity to better predict translation [2]. Wang proposed an English translation model optimization based on machine learning, and achieved certain results [3]. On the basis of previous research on translation models, Shu proposed a Chinese classic English translation model based on the yin-yang shape. The model explained four interrelated and synergistic stages to highlight the uniqueness of the English translation of Chinese classics: similarity based on Chinese and English idea bases; finding modern Chinese and English equivalents of ancient Chinese sequences, figures, and elements; creating meaning in the target language with the help of grammatical metaphors; developing the translator's subjectivity [4]. These methods have many limitations due to differences in language and culture among countries, and they are not practical, so more perfect methods are needed.

In order to make the English translation model adapt to different regions, some scholars have proposed a dynamic model of English translation language propagation based on differential equations, which has strong compatibility and can be applied to different regions. Among them, Likhoshvai and Khlebodarova presented analytical results of stationary solutions of differential equations with two delay parameters, and he described the existence conditions of non-negative solutions. This stability theory allowed a complete characterization of these solutions to be given for all values of the model parameters, and also described the relative stability domain. These points became unstable for certain values of these parameters. Their results showed that the absolute and relative stability domains of the positive equilibrium point shrank while its instability domain expanded as the nonlinearity and complexity of translation efficiency and its regulatory mechanisms increased

[5]. New characteristics for the solution of functional differential equations with linearly changed parameters were developed by Pelyukh and Bel'skii [6]. The asymptotic behavior of solutions to functional differential equations with linearly transformed parameters was also examined by Pelyukh and Bel'skii [7]. In Torrey, Andres investigated the coexistence of impulse differential equations with sub-order harmonic periodic solutions of first-order vector systems [8]. Andres and Pastor also looked into the block-cycle coexistence theorem, which was still used to solve differential equations using the Poincaré translation operator, and all deterministic solutions were randomized in a positive way [9]. Furthermore, using the related Poincaré translation operator, Wong and Giessner investigated the positive topological entropy of impulsive differential equations on compact subsets of Euclidean space, particularly on torus [10]. Although the differential equations studied by the above scholars can be practically applied and expanded to a certain extent, these methods are inefficient, and involve less in the field of English translation. The translation effect is still not ideal, so further improvement is required.

This paper uses the language algorithm of neural networks and differential equations to construct a dynamic model of language propagation, and combines GLM and the domain language model to conduct a comparative test of English translation. The test data come from the EBSCO language database, and the word groups tested are divided into professional and non-professional, as well as the computer field, the medical field, and the economics field. The results show that whether it is a non-professional phrase or a professional phrase, the average code length of the NNLM model in the computer field is the smallest, about 2.2 bits. The average code length of GLM is the longest at 3.4 bits. The average code length of the domain model remains centered. It shows that the NNLM model can process phrases faster and more concisely. Under the non-professional thesaurus, the first word hit rate of GLM is about 75%. The NNLM model is about 85%. The domain language model is about 80%. While under the professional thesaurus, the first word hit rate of GLM is about 80%. The NNLM model is more than 90%. The domain language model is about 85%. It indicates that the NNLM model translation has more advantages. The overall recall rate of the language propagation dynamic model is 79.67%. The accuracy is 86.37%. There are a total of 9705 characteristic phrases translated. It shows that the translation effect of the language propagation dynamic model constructed in this paper is good and has certain feasibility.

Unlike the traditional stuffy research methods, The innovation of this paper is to propose a language model of neural network, and combine the methods of general language model as well as domain language model, in order to construct a dynamic model of language propagation and use differential equations and neural network methods to calculate. Through comparing the translation situations in different fields, the results obtained are more obvious and feasible.

2. Dynamic Model of Language Propagation Based on Differential Equations

2.1. Construction of Dynamic Model of Language Propagation. The translation of traditional language models is rigid and not flexible enough to adapt to multiple environments and cannot perform dynamic translation, so it needs to be improved. The dynamic model architecture of language propagation adopted in this paper is shown in Figure 1. In Figure 1, the searched thesaurus is divided into a word code library, a user thesaurus and a professional thesaurus. Using the dynamic adaptive neural network NNML language model combined with GLM and the domain language model, the translation results are classified. The user makes a judgment, and the model is dynamically updated according to the user's choice [11].

A schematic diagram of the NNLM model structure included in the above dynamic model is shown in Figure 2. In Figure 2, the input words are first classified, corresponding to the specified phrases, and then they are vectorized. The data are maximized according to the hyperbolic tangent activation function, and then normalized according to the softmax function (Softmax function is a single-layer neural network. It is a generalization of the binary classification function sigmoid in multiclassification. Its purpose is to display the results of multiclassification in the form of probability, which can convert linear prediction values into class probabilities) in order to maximize the probability corresponding to the words of the objective function [12].

The NNLM model is able to adapt to language differences, which originate from different cultures, beliefs, and living habits, as shown in Figure 3, due to language differences caused by various cultures, beliefs, living habits, etc., in the process of English translation, using the flexibility of parts of speech to translate can make the expression more accurate. In some cases, Chinese and English can use antonyms to express the same meaning. For example, bei wu can be translated as a room with a southern exposure. The corresponding Chinese word used in the translation here should be south. Apparently, antonyms are used in this translation of the phrase. Such translation can not only express the location of the house clearly, but also take into account the language differences between Chinese and English. From this, people can understand the use of affirmation and negation between languages, and the mutual conversion of meaning between positive and negative. This kind of conversion is quite flexible. If people make good use of the conversion perspective, their translation will not only meet the requirements of the source language, but also make the target language readers not understand biased, so that they can complement each other and get what they need [13, 14].

The most fundamental reason for the difference of language is the different background of language generation. English is a together-form language, while Chinese is a parataxis language. Word order and context can indicate the semantic link between words. The reciprocal conversion of distinct parts of speech is linked with the mutual conversion of different sentence components and clauses in the practice of translation. Understanding this conversion mechanism is quite beneficial in removing the mother tongue's influence. The use of basic, easy-to-understand language to make complicated things simple and plain, making abstract things tangible and vivid, such as characters, animals, numbers, and so on, is known as image. There is no translation without alteration in this sense [15, 16].

In the process of translation, when images with different associative meanings appear, the phenomenon of mutual borrowing is common. The borrowed words supplement and enrich the expression means of the language, as well as retain the original image and meaning. There are also many idioms in Chinese that have been conventional in the minds of Chinese readers, such as castle in the air, which are actually directly introduced from foreign languages. These phrases are frequently used in the media and have now become part of Chinese [17]. Therefore, it is necessary to make flexible use of the differences between the two languages in order to more accurately. In order to achieve this flexible translation method, we can borrow the thinking of differential equations and neural networks to dynamically spread the language and achieve more accurate translation. The following two subsections are visible for the differential equation and the NNLM model.

2.2. Differential Equations. Thinking using differential equations to solve dynamic problems is become common. In the natural and social sciences, differential equations are the most basic mathematical theories and tools for studying the motion and changes of objects. Differential equations can be used to describe many concepts and rules in fields such as physics, chemistry, aerospace, economics, astronomy, automatic control, and economics, for example, the law of gravitation, the design of various electronic devices, ballistic calculations, the study of flight stability of aircraft and missiles, the study of the stability of chemical reaction processes, the law of population growth, the spread of diseases, the rising and falling trends of stocks, the stability of market equilibrium prices change, and so on. The study of mathematical models defined by appropriate differential equations boils down to the description, interpretation, and analysis of these laws. Therefore, the theory and methods of differential equations are increasingly used in social sciences as well as in scientific sciences. They are also becoming more common in various social science fields [18].

Mathematicians first discovered in the subject of differential equations, it is possible to obtain all solutions to the problem if the solution has as many arbitrary elements as possible (that is, arbitrary constants). However, it has become evident that only a few equations can be found analytically to have general solutions. As a boundary condition, the solution of the equation is a constant [19].

The general formula for a differential equation is as formula:

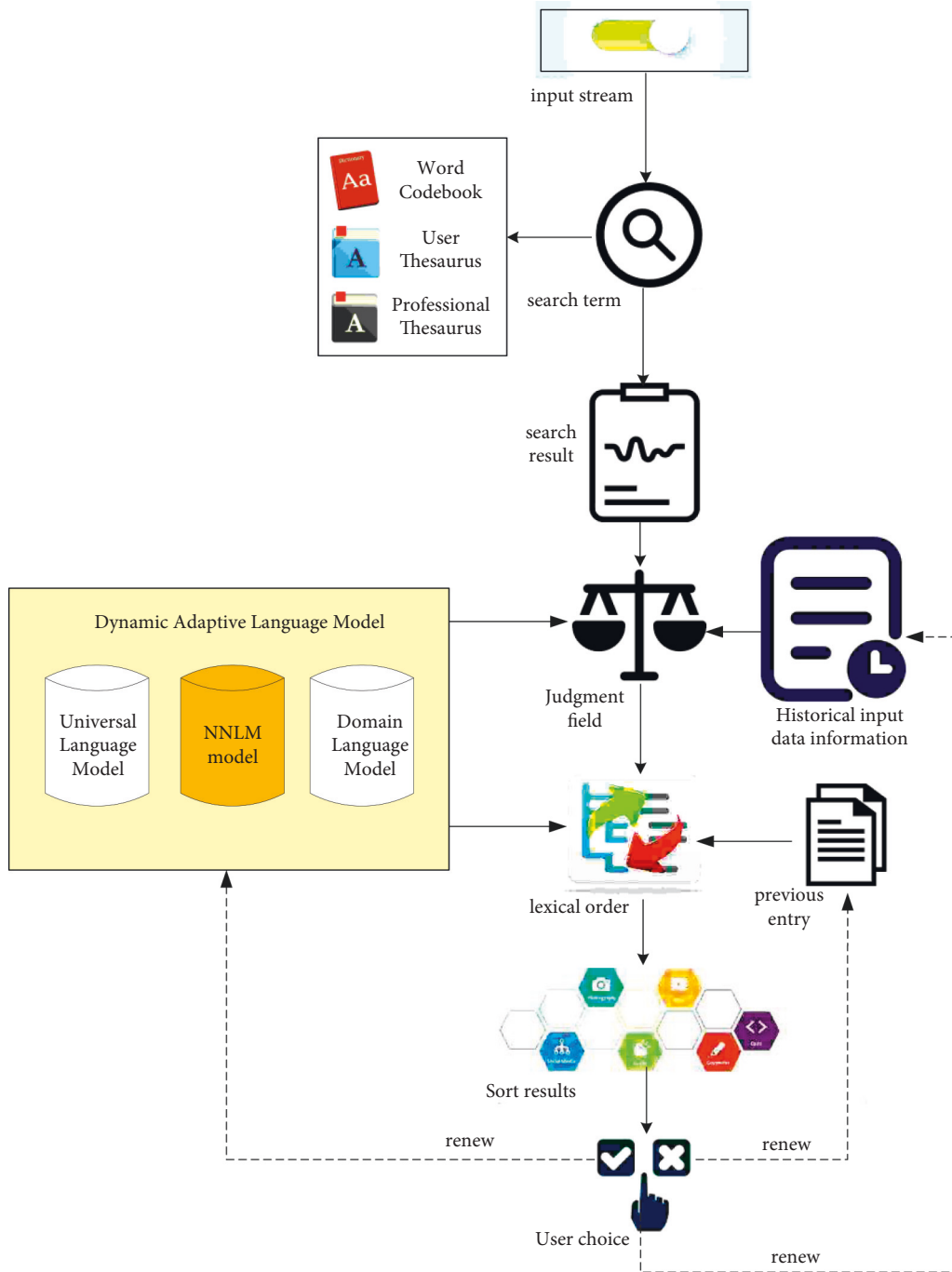$$f\left(x, y, y', y'', \ldots, y^{(n)}\right) = 0. \tag{1}$$

FIGURE 1: Dynamic models of language propagation.

For the nth order differential equation, it can be expressed as formula:

$$F\left(y, \frac{\mathrm{d}y}{\mathrm{d}x}, \ldots, \frac{d^m y}{d x^n}\right) = 0. \qquad (2)$$

Differential equations can correctly define and describe the law of neuron activity and the law of strength and connection between neurons so as to construct the neural network language model used in this paper.

Differential equations can be divided into the following four categories. Their characteristics and differences are shown in Table 1.

Among differential equations, there are very few first-order equations for which a general solution can be found, except for linear equations, equations with separable variables, and equations that are both types of equations in a specific way. Linear equations can still be solved by superposition of higher order equations. That is, a higher order
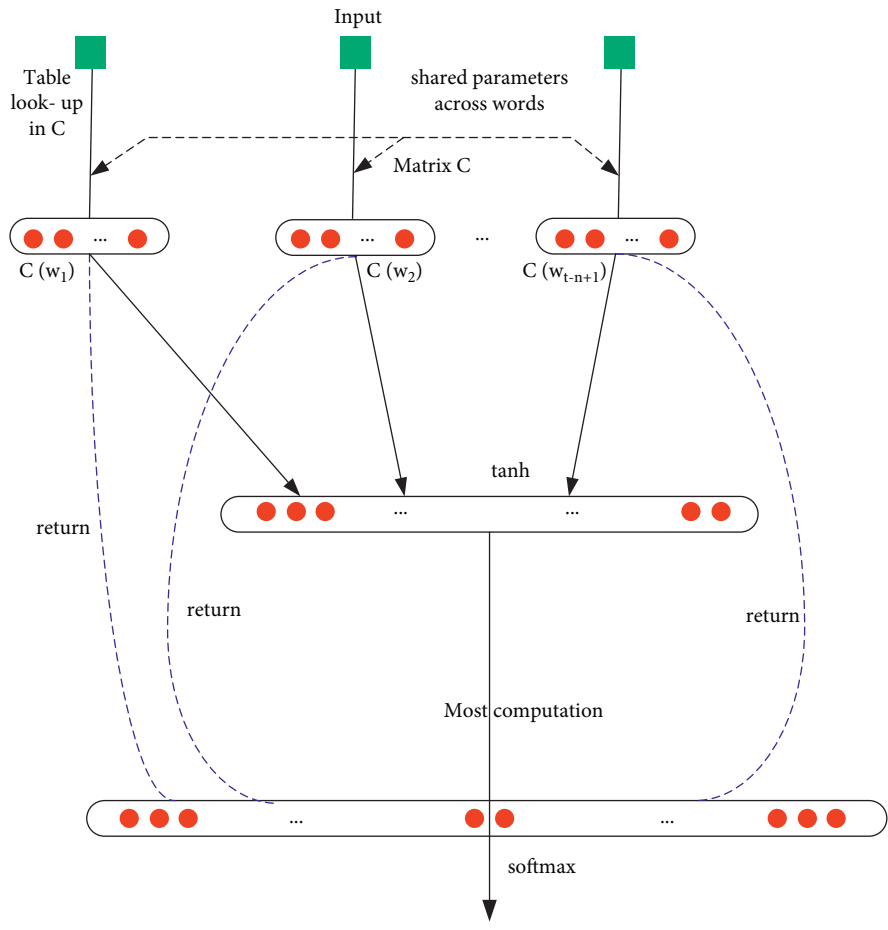
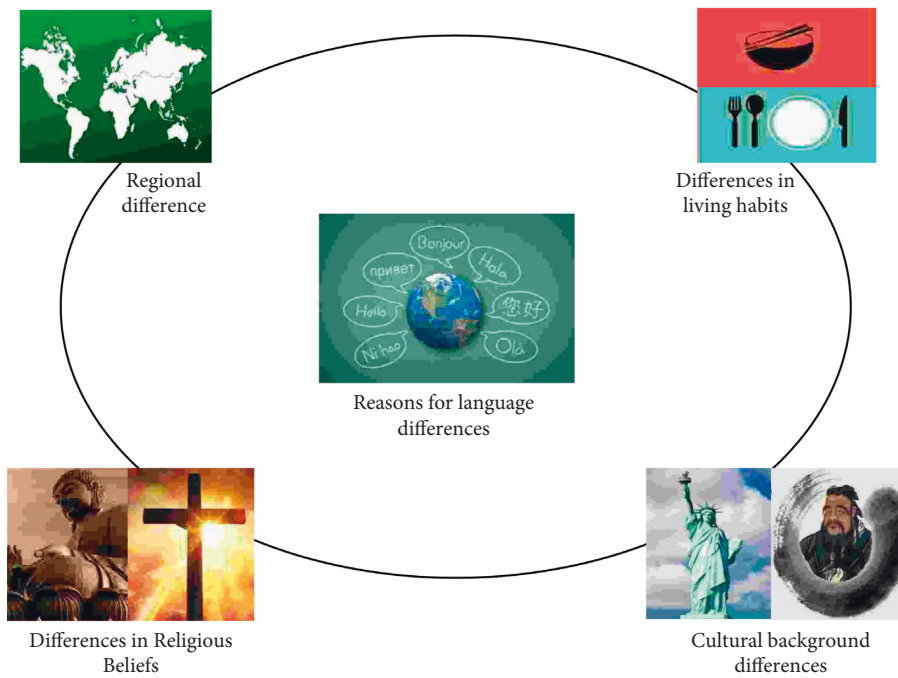Figure 2: Schematic diagram of the NNLM language model.

Figure 3: Sources of language differences.

TABLE 1: Types of differential equations.

Category	Name	Particularity
1	Ordinary disparity	A differential equation with only one independent variable is referred to a one-variable differential equation.
2	Partial differential	A differential equation with two or more independent variables, and the equation contains an unknown partial derivative to the independent variable.
3	Linear differentiation	If F above is a rational expression, then equation F is called a linear equation of degree n.
4	Nonlinear differentiation	If the above F is not a rational expression, then equation F is called a nonlinear equation.

homogeneous equation's general solution is a linear combination of its independent special solutions, the coefficients of which are arbitrary constants. The inhomogeneous equation's general solution is equal to the corresponding flushing equation's general solution plus the inhomogeneous equation's special solution, which can also be obtained by the constant variation method. When the coefficients are constant, the answer can be reduced to finding the roots of the algebraic equation in the order of the original equation. Only two very unusual cases (Eulerian and Laplace's equations; Euler's equation, the differential equation of motion, is one of the most important fundamental equations in inviscid fluid dynamics, which refers to the differential equation of motion obtained by applying Newton's second law to inviscid fluid micelles. Laplace equation, also known as harmonic equation and potential equation, is a kind of partial differential equation. Laplace equation expresses the relationship between liquid surface curvature and liquid surface pressure) can be obtained when the coefficients are changed. There are few general solutions available for nonlinear higher order equations, except in a few cases where the order can be reduced. This problem can be solved first, and then the exact answer can be estimated using the local numerical solution of the differential equation. Therefore, the numerical solution of differential equations has a wide range of uses [20]. However, relying only on differential equations cannot fully understand the way of language dynamic propagation, and needs to combine the more intelligent language model for dynamic analysis, while NNLM model is an intelligent neural network language model, which is detailed in the next subsection.

2.3. NNLM Language Model.

The NNLM language model utilizes the intelligent analysis method of neural networks to enables dynamic propagation of language. Figure 4 depicts the neural network model structure employed in the NNLM language model. The input layer is to input the words to be translated. The projection layer is to vectorize and standardize the phrase to obtain a data matrix. The hidden layer performs function activation on the vector and obtains the matrix weights. The output layer obtains the translation results obtained through network analysis, and performs regression analysis according to the results to make the results more accurate.

For an unknown input x, it can be expressed in vector space as formulas (3) and (4):

$$x = [V(\omega_i)|V(\omega_{i+1})|\ldots|V(\omega_{i+n-1})], \quad (3)$$

$$h = \tanh(U * x + b^1). \quad (4)$$

In formulas (3) and (4), V is a vector; n is the number of words in the database; U and b are the correlation coefficients.

The output y can be expressed as formula:

$$y = W * h + b^2. \quad (5)$$

According to the neural network, the learning methods are as formulas (6) and (7):

$$p = \frac{\exp y}{\sum_{i=1}^{n} \exp y_i}, \quad (6)$$

$$P(\omega_i) = p_{\omega i}[\omega i + \mathrm{win}] = \frac{\exp y_{\omega i + \mathrm{win}}}{\sum_{i=1}^{n} \exp y_i}. \quad (7)$$

In formulas (6) and (7), ω represents the word; win represents the number of windows; p represents the output of each training data, which is related to the previous output value.

For the prediction bias of the model, it can be expressed as formula:

$$e = \sum_{i}^{M} \log P(\omega_i). \quad (8)$$

For the back-propagation process of the neural network, the derivation method can be used, and the general derivation method is as formula:

$$\frac{\partial x}{\partial Y} = \left(\frac{\partial x}{\partial y_1} \cdots \frac{\partial x}{\partial y_n}\right)'. \quad (9)$$

If Y is a data matrix as formula:

$$Y = \begin{bmatrix} y_{11} & \cdots & y_{1n} \\ \vdots & \ddots & \vdots \\ y_{n1} & \cdots & y_{nn} \end{bmatrix}, \quad (10)$$

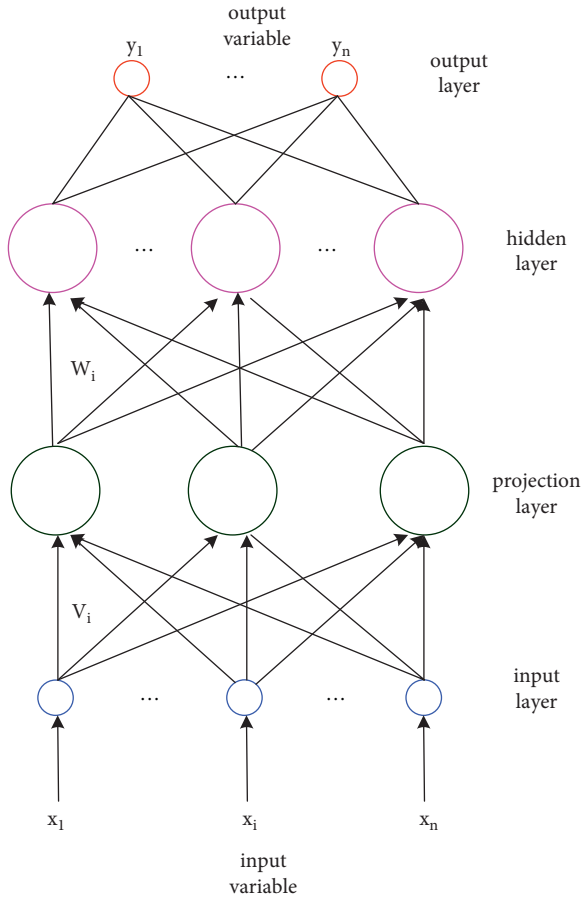then its derivation is as formula:

FIGURE 4: Neural network structure.

$$\frac{\partial x}{\partial Y} = \begin{bmatrix} \dfrac{\partial x}{\partial y_{11}} & \cdots & \dfrac{\partial x}{\partial y_{1n}} \\ \vdots & \ddots & \vdots \\ \dfrac{\partial x}{\partial y_{n1}} & \cdots & \dfrac{\partial x}{\partial y_{nn}} \end{bmatrix}. \tag{11}$$

Similarly, for the deviation function e, the derivative is as formula:

$$\frac{\partial e}{\partial y_i} = \begin{cases} 1 - p_i, & \omega i + \text{win} = i \\ -p_i, & \text{else} \end{cases}. \tag{12}$$

Then the derivative of the related elements of b is taken. Because the two correspond, there are:

$$\frac{\partial e}{\partial b^2} = \frac{\partial e}{\partial Y}. \tag{13}$$

Then according to the chain rule (The chain rule is the derivative rule in calculus, which is used to find the derivative of a composite function. The so-called compound function refers to one function as the independent variable of another function. The derivative of the composite function will be the product of the derivatives of the finite number of functions that constitute the composite function

at the corresponding points), the partial derivatives of the deviation functions e and h can be obtained as formula:

$$\frac{\partial e}{\partial h} = W' \cdot \frac{\partial e'}{\partial Y}. \tag{14}$$

Then h is derived with respect to b:

$$\frac{\partial h}{\partial b^1} = \left(1 - h^2\right). \tag{15}$$

The deviation function e is derived with respect to the hidden layer H:

$$\frac{\partial e}{\partial H_j} = \frac{\partial e}{\partial b_j^1} \cdot x'. \tag{16}$$

Finally, the deviation function e is derived from the input value x to get formula:

$$\frac{\partial e}{\partial x} = H' \cdot \frac{\partial e'}{\partial b_j^1}. \tag{17}$$

At last, updating each parameter is adding a bias e to each partial derivative of the variable.

3. English Translation Simulation Experiment Based on Dynamic Model of Language Propagation Determination of

Each Model and Thesaurus: According to the overall architecture of the language propagation dynamic model designed above, it is known that the model includes multiple models, as exemplified in Table 2. This paper will further improve and determine the input model, general language model and domain language model.

3.1. Input Model. The input model included in the model in this paper is shown in Figure 5, which includes the input window, the input data set processing sub-model, the dynamic storage sub-model, the thesaurus sub-model, and finally the input interface. This model is used for dynamic input to language translation models. The user interacts with the input system through the input window. The input window receives the user's input request and transmits it to the input stream processing model, and then feeds the result back to the user. The input stream processing model mainly receives and processes characters input from users, including input codes, function symbols, and so on. The system performs different processing methods according to different input characters. The word codebook file and the domain thesaurus are the basic data structures of the input system. Using it to store the data can realize the conversion from the input code to the internal code, and the user thesaurus stores the word codebook entered by the user and the phrases that do not exist in the thesaurus file.

3.2. Universal Language Model. Universal language model is a language model used in a common case. Because the storage space required by GLM is particularly large, this paper uses the binary grammar model suitable for tailoring to reduce the size of its data, as seen in Figure 6. ICTCLAS (It

TABLE 2: Model summary.

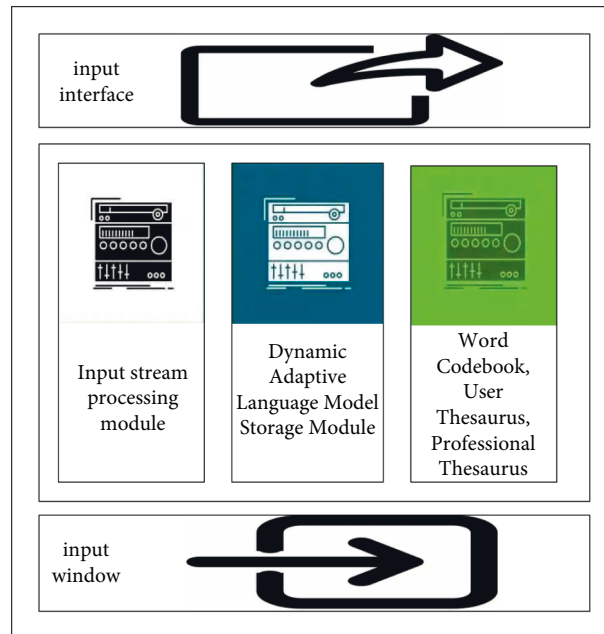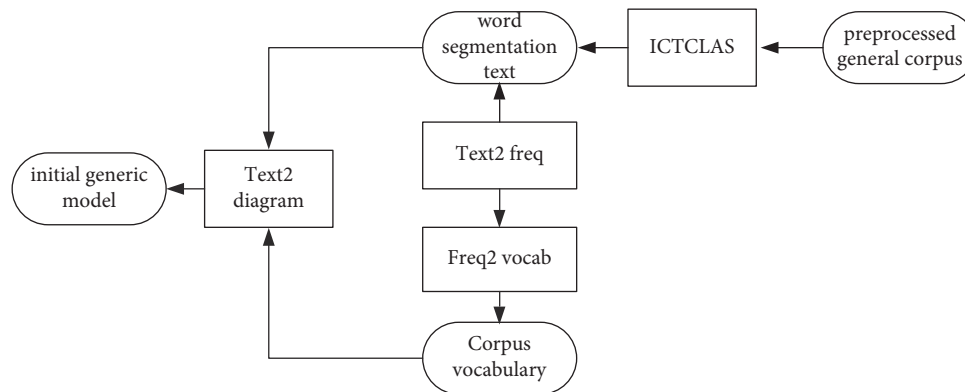| Module number	Module content
1	Input module
2	Common language module
3	NNML module
4	Domain language module

FIGURE 5: Input model.

FIGURE 6: Universal language model.

is a Chinese lexical analysis system. Its functions include Chinese word segmentation, part-of-speech tagging, named entity recognition, new word recognition. At the same time, it supports user dictionaries and is the best Chinese lexical analyzer in the world.) is a word segmentation tool, and its open-source code is modified to complete the word segmentation task for many phrases.

3.3. Domain Language Model. As shown in Figure 7, this paper also uses the binary model to reduce the size of its data according to the currently selected phrases in several popular

fields, and the binary domain model of this paper is obtained.

This paper selects phrases from three major fields of medicine, economics, and computer science from the EBSCO language database. The number of phrases selected in each field is shown in Table 3. The number of phrases selected in the three fields is similar, all around 30,000, of which the medical category is a bit more, about 32,000. Probably due to the impact of the epidemic, there have been more medical phrases recently.

In addition, considering the coexistence of fields between phrases, this paper makes statistics on these phrases
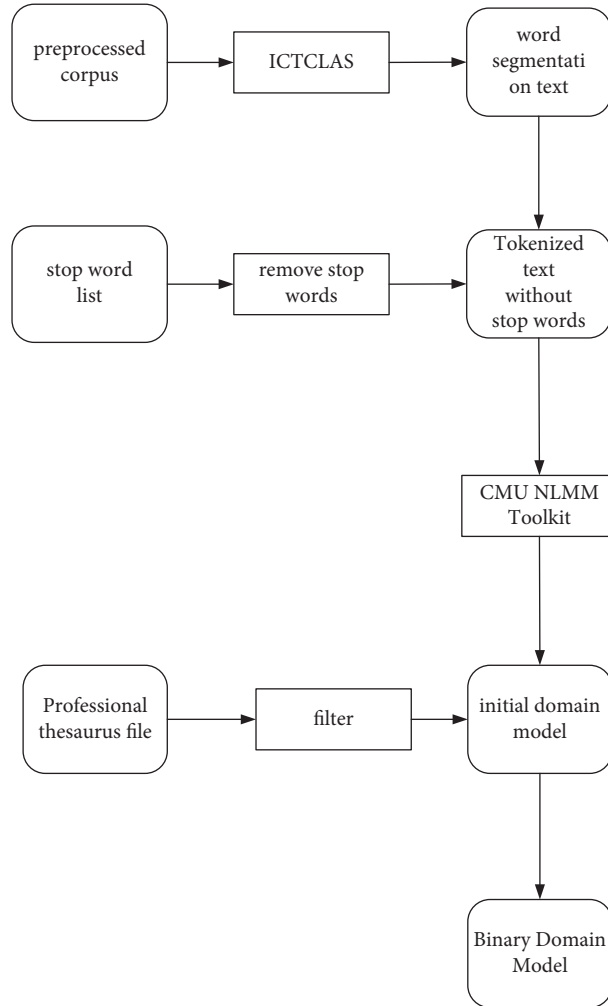
FIGURE 7: Domain language model.

TABLE 3: Domain vocabulary.

Domain	Word size (number of entries)
Medicine	32011
Economy	29876
Computer	29975

TABLE 4: Coexisting domain phrases in the corpus.

Domain	Coexistence
Medicine	2851
Economy	2723
Computer	2072
Total	7646

selected from the EBSCO language data database. As shown in Table 4, there are a total of 7646 coexisting phrases. The purpose of counting coexisting phrases is to make the calculation of subsequent results more accurate.

4. Experimental Testing This article is tested against data

selected from the EBSCO database. The average code length of each language model in the computer field, the economic field and the medical field is obtained under the professional phrases and non-professional phrases, as seen in Figure 8. Figure 8 illustrates that whether it is a non-professional phrase or a professional phrase, the average code length of the NNLM model in the computer

field is the smallest, about 2.2 bits. The average code length of GLM is the longest at 3.4 bits. The average code length of the domain model remains centered. This shows that the NNLM model can process phrases more compactly and faster. Moreover, the average code length of each language model under professional phrases is smaller than that of non-professional phrases, because the translation of professional phrases has high specificity and is easy to be recognized by the model.

In addition, according to the translation records of the model stored in the model, the first word hit rate of each phrase translation can be obtained by statistics, as seen in Figure 9. As can be seen from Figure 9, under the non-professional thesaurus, the first word hit rate of GLM is about 75%. The NNLM model is about 85%. The domain
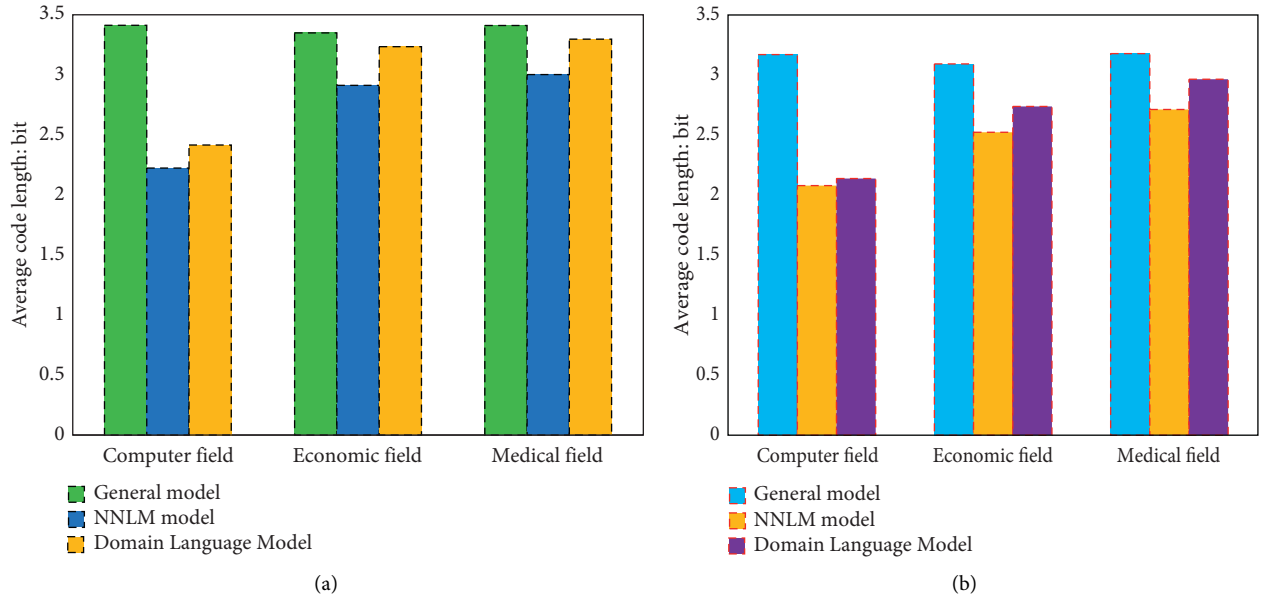
FIGURE 8: Average code length of each language model in different domains. (a)Average code length under non-specialized phrases. (b) Average yardage under specialized phrases.
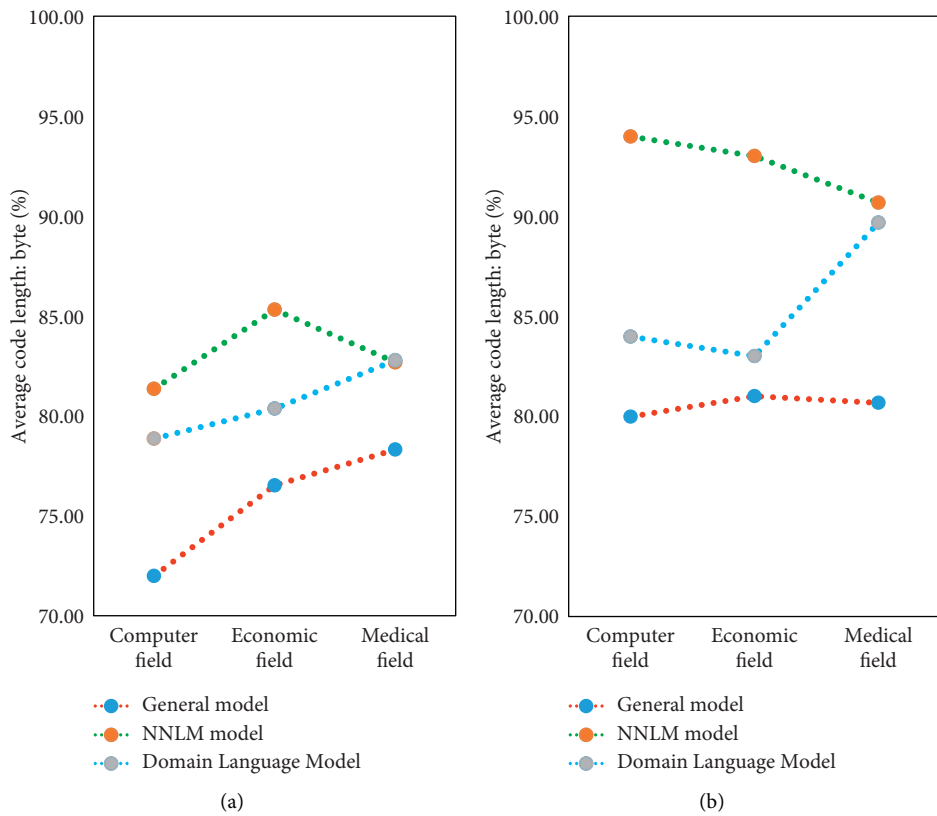

FIGURE 9: Translation first word hit rate of each model in the three domains. (a) Non-professional thesaurus. (b) Professional thesaurus.
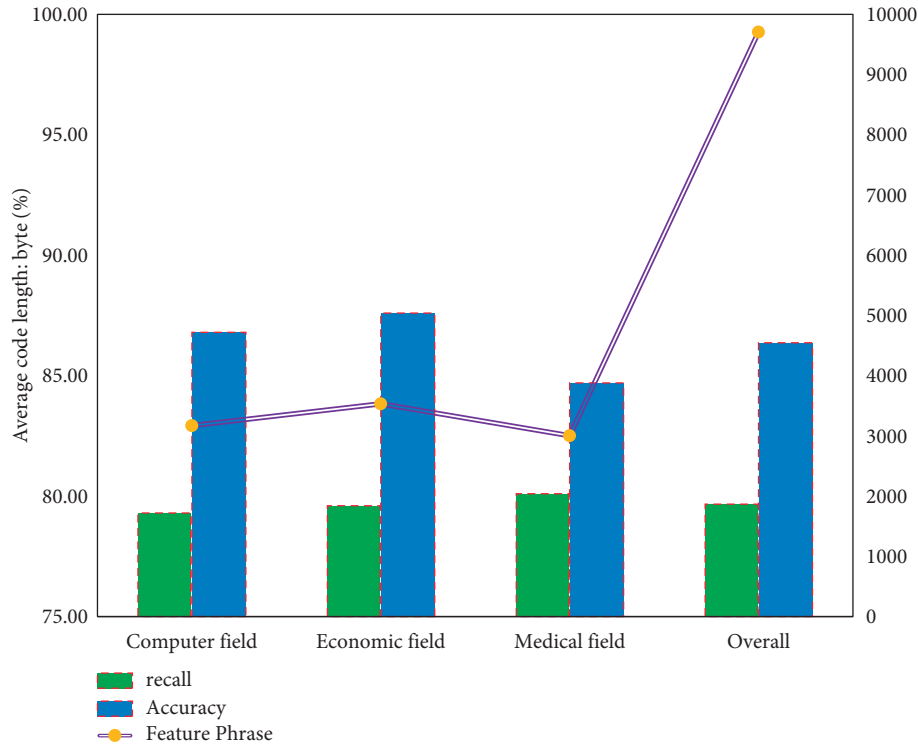
FIGURE 10: Overall translation effect of the language dynamic model.

language model is about 80%. Under the professional the-saurus, the first word hit rate of GLM is about 80%. The NNLM model is more than 90%. The domain language model is about 85%. Because the NNLM model has the adaptive feedback learning ability, it has more advantages in the translation of the first word, and the language translation correspondence is high under the professional thesaurus. Therefore, the first word hit rate is generally higher than that of non-professional thesaurus.

Finally, according to the previous data, the overall translation effect of the language dynamic model combined with GLM, the domain language model and the NNLM model is obtained, including its accuracy, recall, and number of feature phrases, as seen in Figure 10. Figure 10 illustrates that the overall recall rate of the model is 79.67%. The ac-curacy is 86.37%. There are a total of 9705 characteristic phrases translated. It shows that the dynamic model of language propagation constructed in this paper has certain feasibility.

5. Conclusions

Through using the language dynamic model constructed in this paper for English translation, it is known that the av-erage code length of the NNLM model in the computer field is the smallest whether it is a non-professional phrase or a professional phrase. This shows that the NNLM model can process phrases more concisely and faster. Because of the high specificity of professional phrase translation, it is easy to be recognized by the model and translated accurately. The

average code length of each language model under profes-sional phrases is smaller than that of non-professional phrases. Because of the adaptive feedback learning ability of the NNLM model, its initial hit rate is relatively higher than other language models. Finally, the dynamic model of language propagation constructed in this paper has relatively high recall rate and accuracy rate, and it can also identify a large number of characteristic phrases. This shows that the translation effect of the language propagation dynamic model constructed in this paper is good and has certain feasibility.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

References

[1] K. Kim, E. J. Park, J. H. Shin, O. W. Kwon, and Y. K. Kim, "Divergence-based fine pruning of phrase-based statistical translation model," *Computer Speech & Language*, vol. 41, pp. 146–160, 2017.

[2] K. Chen, T. Zhao, M. Yang et al., "A neural approach to source dependence based context model for statistical machine translation," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 26, no. 2, pp. 266–280, 2018.

[3] L. Wang, "Retracted article: urban land ecological evaluation and English translation model optimization based on machine learning," *Arabian Journal of Geosciences*, vol. 14, no. 11, pp. 1023–1031, 2021.

[4] H. Shu, "A model for English translation of Chinese classics," *Language and Semiotic Studies*, vol. 4, no. 04, pp. 109–133, 2018.

[5] V. A. Likhoshvai and T. M. Khlebodarova, "On stationary solutions of delay differential equations: a model of local translation in synapses," *Mathematical Biology and Bioinformatics*, vol. 14, no. 2, pp. 554–569, 2019.

[6] G. P. Pelyukh and D. V. Bel'skii, "Asymptotic properties of the solutions of functional-differential equation with linearly transformed argument," *Journal of Mathematical Sciences*, vol. 243, no. 2, pp. 240–278, 2019.

[7] G. P. Pelyukh and D. V. Bel'skii, "Asymptotic behavior of the solutions of a functional-differential equation with linearly transformed argument," *Ukrainian Mathematical Journal*, vol. 72, no. 1, pp. 78–97, 2020.

[8] J. Andres, "Coexistence of periodic solutions with various periods of impulsive differential equations and inclusions on tori via Poincaré operators," *Topology and its Applications*, vol. 255, pp. 126–140, 2019.

[9] J. Andres and K. Pastor, "Sharp block-sharkovsky type theorem for multivalued maps on the circle and its application to differential equations and inclusions," *International Journal of Bifurcation and Chaos*, vol. 29, no. 09, pp. 1950127–1950417, 2019.

[10] S. I. Wong and S. R. Giessner, "The thin line between empowering and laissez-faire leadership: an expectancy-match perspective," *Journal of Management*, vol. 44, no. 2, pp. 757–783, 2018.

[11] V. H. Linh and R. Marz, "Adjoint pairs of differential-algebraic equations and their lyapunov exponents," *Journal of Dynamics and Differential Equations*, vol. 29, no. 2, pp. 655–684, 2017.

[12] V. A. Beloshapko, E. A. Generalov, and L. V. Yakovenko, "Model of cell activation through TLR4 and TNFR2 receptors," *Moscow University Physics Bulletin*, vol. 74, no. 6, pp. 662–668, 2020.

[13] Q. J. Li, R. R. Wu, and Y. Ng, "Developing culturally effective strategies for Chinese to English geotourism translation by corpus-based interdisciplinary translation analysis," *Geoheritage*, vol. 14, no. 1, pp. 6–24, 2022.

[14] V. Z. Grines, E. Y. Gurevich, and O. V. Pochinka, "A combinatorial invariant of morse-smale diffeomorphisms without heteroclinic intersections on the sphere Sn, n ≥ 4," *Mathematical Notes*, vol. 105, no. 1-2, pp. 132–136, 2019.

[15] N. Jha and S. Perera, "Editorial," *Differential Equations and Dynamical Systems*, vol. 28, no. 3, p. 513, 2020.

[16] V. B. . Cherepennikov, "Smooth solutions to some differential-difference equations," *Journal of Mathematical Sciences*, vol. 230, no. 5, pp. 786–789, 2018.

[17] J. Wang and Z. Chen, "Limiting directions of julia sets of entire solutions to complex differential equations," *Acta Mathematica Scientia*, vol. 37, no. 1, pp. 97–107, 2017.

[18] B. Long and C. Zhu, "The periodic solutions bifurcated from a homoclinic solution for parabolic differential equations," *Discrete and Continuous Dynamical Systems - Series B*, vol. 21, no. 10, pp. 3793–3808, 2016.

[19] M. A. Zemirni and B. Belaïdi, "[p, q]-order of solutions of complex differential equations in a sector of the unit disc," *Annals of the University of Craiova*, vol. 45, no. 1, pp. 37–49, 2018.

[20] I. Adam Muhammad Nur and A. Muhammad Nur, "English - Sundanese translation," *International Journal of English and Literature*, vol. 8, no. 2, pp. 9–14, 2018.