Journal of Modern Physics, 2022, 13, 518-573
https://www.scirp.org/journal/jmp
ISSN Online: 2153-120X
ISSN Print: 2153-1196

Experimental Verification of the Theory of Non-Force (Information) Interaction

Iurii Teslia

Department of Information Technology of Design, Cherkasy State Technological University, Cherkasy, Ukraine
Email: dr.teslia@gmail.com

How to cite this paper: Teslia, I. (2022) Experimental Verification of the Theory of Non-Force (Information) Interaction. *Journal of Modern Physics*, **13**, 518-573.
https://doi.org/10.4236/jmp.2022.134034

Received: March 10, 2022
Accepted: April 26, 2022
Published: April 29, 2022

Abstract

The work is devoted to the demonstration of the possibility of applying the formulas of information handling obtained in the theory of non-force interaction for the natural language processing. These formulas were obtained in computer experiments in modelling the movement and interaction of material objects by changing the amount of information that triggers this movement. The hypothesis, objective and tasks of the experimental research were defined. The methods and software tools were developed to conduct the experiments. To compare different results of the simulation of the processes in a human brain during speech production, there was a range of methods proposed to calculate the estimate of sequence of fragments of natural language texts including the methods based on linear approximation. The experiments confirmed that the formulas of information handling obtained in the theory of non-force interaction reflect the processes of language formation. It is shown that the offered approach can successfully be used to create systems of reactive artificial intelligence machines. Experimental and, presented in this work, practical results constitute that the non-force (informational) interaction formulae are generally valid.

Keywords

Non-Force Interaction, Non-Force Interaction Method, Computer Linguistics, Mechanical Movement, Special Relativity

1. Introduction

Information is the basis of a human life. Can it be that it is the source of the Universe's existence? Can the Universe be digital, computable? Today there is a range of theories that declare this variant of world formation, particularly, the computer simulation hypothesis of Nick Bostrom [1], or the research of the laws of physics as a cellular automaton by Stephen Wolfram and Nobel laureate Gerard't Hooft [2] [3]. But, unfortunately, these, as well as other similar theories, have not been proven experimentally yet.

One of these theories is the non-force interaction theory (NFIT). It is based on a computer model in which the source of movement is information that triggers the movement [4] [5] [6], not only at social, biological or technical level of the matter existence, but also the mechanical movement of any material objects. If information is the basis of the Universe's existence, it should definitely manifest itself in mechanical movement as movement is a general form of the existence of matter. The NFIT is built on the information-probabilistic interpretation of movement. There are formulae received that correspond to Newton's classical and Einstein's relativistic mechanics with one addition that the source of movement is the information. Therefore, during interaction informational contents changes first, which then leads to changes in movement (speaking about mechanical movement, it leads to changes in the direction and speed of movement).

The research purpose of the work is to confirm the hypothesis of the theory of non-force interaction, which claims that all interactions in nature are based on informational reasons and are described by the same formulas. For this purpose, it is offered to verify the correspondence of the formulae received in the theory of non-force interaction to informational processes of speech production in a human brain by the means of computer experiments. The main question the answer to which is given in the article through experimental research is that probabilities of sequence of letter combinations in the texts in different languages can be received from the formulae of non-force interaction, which in their turn were received from information-probabilistic interpretation of mechanical movement.

If we can confirm it, it will mean that, when forming natural language texts, the processes of interaction in a human brain correspond to the formulae received in the theory of non-force interaction. This, therefore, will prove the universality of these formulae, and therefore, the validity of the results received from the theory of non-force interaction. Moreover, the main aspect is that this will significantly prove the hypothesis of the theory that all interactions in the Nature are caused by informational reasons.

2. Primary Research Materials

2.1. General Information about Non-Force Interaction Theory

The theory of non-force (information) interaction gives information-probabilistic interpretation of the laws that describe mechanical movement and immediate interaction of material objects. To do this, one more parameter was introduced into the non-force interaction theory: information that triggers the movement. On the basis of this, the formulae of transformation of information contents of the objects during their interaction were received from the known laws of physics. These formulae were obtained based on the following logical conclusions:

1) The theory of non-force interaction is based on the thesis that each object has a memory that contains information about previous interactions and that motivates it to move. Geometrically, memory is represented by the areas of determining the direction of movement of the object (**Figure 1**). The greater the difference in the amount of information that triggers the movement of two objects, the greater the relative velocity of the objects.

2) In the non-force interaction theoryphysical fields [7] provide information that triggers the movement. Field is not physical, but informational category. It is important what information the field can transfer rather than how it is done. **Physical field is the carrier of information and not the source of forceful action.**

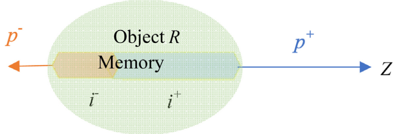
3) The movement of objects is determined not by physical laws, but by their "ability to react correctly" to the existence of other objects and which was formed during 13.8 billion years. In almost 13.8 billion years the matter learned to react to other objects exactly as it does when it changes the direction and velocity of movement during interaction. Physics explains the movementby the constant physical laws of the Nature. However, in the non-force interaction theory the movementis information.

4) We provide information to other people through speech. This information changes (complements) their available information. Such changed information triggers changes in the "movement" (actions) of people. Now, let us use the method of analogies. Physical fields "provide" information to the objects about the existence of other objects. The changed amount of information that triggers the movement, triggers the changes in mechanical movement (direction and velocity).

5) During the interaction of material objects, their amount of information that triggers the movement changes first, which then leads to the changes in their movement.

6) From the known "physical laws" there can be received the laws of change of the amount of information that triggers the movement, during interaction.

7) In the non-force interaction theory, the movement of the object is interpreted by shifts in possible directions (one quantum of space per one quantum of time). The probability of the shift is determined by the amount of information that triggers the movement [4] [5]. For a one-dimension movement in direction Z (**Figure 1**) [5].



i^+ - the size of the area to determine the movement in the direction Z;
i^- - the size of the area to determine the movement in direction opposite to Z;
p^+ - probability of a shift in direction Z;
p^- - probability of a shift in direction opposite to Z.

Figure 1. Information-probabilistic model of mechanical movement.

8) On **Figure 1**, the formulae that are proposed in the non-force interaction theory [4] are stated to calculate the probability of a shift.

$$p^{+} = \frac{i^{+}}{i^{-} + i^{+}};\ p^{-} = \frac{i^{-}}{i^{-} + i^{+}}. \tag{1}$$

They are based on the geometrical representation of the ranges of definition of the object movement, that are in the object's memory (**Figure 1**).

9) In the NFIT, the difference in the size of the ranges is called the amount of information that triggers the movement and the addition is the awareness:

$$\begin{aligned} &d = i^{+} - i^{-} \text{ - the amount of information that triggers the movement;} \\ &i = i^{+} + i^{-} \text{ - awareness.} \end{aligned} \tag{2}$$

10) The amount of information that triggers the movement ≡ information about movement direction collected in interactions = non-force (information) influence on the object as to the choice of this exact movement direction.

11) Awareness ≡ information about movement direction collected in interactions = non-force (information) influence on the object as to possible movement directions.

12) Expected drift velocity (or just velocity) of an object (see **Figure 1**) [5]

$$\boldsymbol{V} = \left(p^{+} - p^{-}\right)\cdot \boldsymbol{c} = \left(2\cdot p^{+} - 1\right)\cdot \boldsymbol{c}, \tag{3}$$

where V is expected drift velocity of an object; c is the speed of light in vacuum.

13) The drift velocity of one object regarding the drift velocity of another object is the relative movement velocity.

14) Relative velocity from the formula of relativistic addition of velocities [7] in the information-probabilistic interpretation of mechanical movement looks as follows (using Formula (3)) [5]:

$$\Delta \boldsymbol{V} = \frac{\boldsymbol{V}_2 - \boldsymbol{V}_1}{1 - \frac{\boldsymbol{V}_1 \cdot \boldsymbol{V}_2}{\boldsymbol{c}^2}} \to \frac{p_2 \cdot (1 - p_1) - p_1 \cdot (1 - p_2)}{p_2 \cdot (1 - p_1) + p_1 \cdot (1 - p_2)} \cdot \boldsymbol{c}, \tag{4}$$

where $\Delta \boldsymbol{V}$ is relative velocity of some object R_2 in relation to the object R_1; p_2 is probability of the shift of object R_2 in the direction in relation to which the difference in velocities is measured; p_1 is probability of the shift of object R_1 in the direction in relation to which the difference in velocities is measured; c is the speed of light in vacuum.

However, from (3) it follows:

$$\Delta \boldsymbol{V} = \left(2\cdot \Delta p - 1\right)\cdot \boldsymbol{c}, \tag{5}$$

where Δp is probability of the shift of object R_2 in relation to object R_1 in the direction, in relation to which the difference in velocities is measured.

Then, the probability of the shift of object R_2 which would be "measured" by the observer who is in object R_1 (shift in the direction "away from the observer") from (4) and (5) is [1]

$$\Delta p = \frac{p_2 \cdot (1 - p_1)}{p_2 \cdot (1 - p_1) + p_1 \cdot (1 - p_2)}. \tag{6}$$

15) In the non-force interaction theory [4], it is shown that the implementation of mechanical movement according to Formula (6) is possible only under the condition that the ratio of quantity of actual shifts of all objects one in relation to another will be equal to the ratio of the sizes of definition rangesof motion (see **Figure 1**). However, it is only possible in the situation:

$$i^{+} \cdot i^{-} = const.$$

Based on the commonly used representation of formulae in relativistic mechanics [7], it is convenient to accept that [4]:

$$i^{+} \cdot i^{-} = 0.25. \tag{7}$$

Then from (1), (2) and (7) the connection between the probability of shift in direction (p), the amount of information that triggers the movement (d) and awareness as to the directions of shift (i) in one-dimensional virtual space is defined by the following formulae [1]:

$$i = \frac{1}{2\sqrt{p \cdot (1-p)}}; \tag{8}$$

$$i = \sqrt{d^2 + 1}; \tag{9}$$

$$d = \pm\sqrt{i^2 - 1}; \tag{10}$$

$$d = \begin{cases} 0.5 \cdot \sqrt{\dfrac{p}{1-p} + \dfrac{1-p}{p} - 2}, & p \geq 0.5 \\ -0.5 \cdot \sqrt{\dfrac{p}{1-p} + \dfrac{1-p}{p} - 2}, & p < 0.5 \end{cases} \tag{11}$$

$$p = 0.5 + \frac{d}{2i}. \tag{12}$$

2.2. Velocity and Momentum in Non-Force Interaction Theory

In the core of the non-force interaction theory, there is a computer model of mechanical movement in which the shift of objects one in relation to another is explained by the difference in the amount of information that triggers the movement, as it is shown in Sub-section 2.1. In essence, the non-force interaction theory interprets mechanical movement of material objects "in a new way". Physical categories, such as velocity and momentum, are interpreted through the information that triggers the movement. Accordingly, physical formulae that include these values are represented in a new way, through the amount of information that triggers the movement. Thus, such their interpretation creates possibility to find analogies and check for conformity with informational interaction of people. Let us look at the following interpretation:

1) Representation of physical formulae through the amount of information that triggers the movement:

a) Applying in (12) Formula (3), new representation of velocity formula:

$$\boldsymbol{V} = \frac{d}{i} \cdot \boldsymbol{c}. \tag{13}$$

b) Relativistic mass [7]

$$m = \frac{m_0}{\sqrt{1 - \frac{\boldsymbol{V}^2}{\boldsymbol{c}^2}}}, \tag{14}$$

where m_0 is the mass in the state of rest.

Applying in (14) Formula (13), information-probabilistic interpretation of relativistic mass is obtained [1].

$$m = \frac{m_0}{\sqrt{1 - \frac{\boldsymbol{V}^2}{\boldsymbol{c}^2}}} = \frac{m_0}{\sqrt{1 - \frac{d^2 \cdot \boldsymbol{c}^2}{i^2 \cdot \boldsymbol{c}^2}}} = \frac{m_0 \cdot i}{\sqrt{i^2 - d^2}} = m_0 \cdot i. \tag{15}$$

c) The law of conservation of momentum (quantity of movement). It characterizes mechanical interaction of material objects. It determines that in a closed system the total momentum of all bodies is preserved [8]:

$$\sum_j \boldsymbol{P}_j = const, \tag{16}$$

where $\boldsymbol{P}_i$ is momentum.

$$\boldsymbol{P}_j = m_j \boldsymbol{V}_j, \tag{17}$$

where m_j is mass; $\boldsymbol{V}_j$ is velocity.

Applying in (17) Formulae (13) and (15), it is obtained

$$\boldsymbol{P}_j = m_{0j} \cdot i \cdot \frac{d_j}{i} \boldsymbol{c} = m_{0j} \cdot d_j \cdot \boldsymbol{c},$$

where m_{0j} is rest mass; d_j is the amount of information that triggers the movement.

Hence, information-probabilistic interpretation of the law of conservation of momentum can be stated [4]:

$$\sum_j \boldsymbol{P}_j = \sum_j m_{0j} \cdot d_j \cdot \boldsymbol{c} = const.$$

Out of the fact that in a closed system the total rest mass does not change, the "law of conservation of the amount of information that triggers movement" arises [4]:

$$\sum_j d_j = const. \tag{18}$$

d) The difference in velocity is a consequence of the difference in the amount of information that triggers the movement. In the work [4] it is shown that if (13)

$$\boldsymbol{V}_1 = \frac{d_1}{i_1} \cdot \boldsymbol{c};$$

$$\boldsymbol{V}_2 = \frac{d_2}{i_2} \cdot \boldsymbol{c};$$

$$\Delta \boldsymbol{V}_1 = \frac{\Delta d_1}{\Delta i_1} \cdot \boldsymbol{c},$$

where $\boldsymbol{V}_1$ is the drift velocity of object R_1; $\boldsymbol{V}_2$ is the drift velocity of object R_2; d_2 is the amount of information that triggers the movementof object R_2; d_1 is the amount of information that triggers the movementof object R_1; i_1 is awareness of object R_1, then from Formulas (2) - (4) it is possible to obtain [4]

$$\Delta d = d_2 i_1 - d_1 i_2, \tag{19}$$

where Δd is the difference in determination of objects R_2 and R_1 in relation to the movement in direction Z.

Having d_1 and Δd known, it is possible to determine d_2. See this from (9)

$$i_1 = \sqrt{d_1^2 + 1};$$

$$i_2 = \sqrt{d_2^2 + 1};$$

$$\Delta i = \sqrt{\Delta d^2 + 1},$$

where Δi is the difference in the amount of information that triggers the movement of objects R_1 and R_2.

Then, from (9) it follows

$$d_2 = d_1 \Delta i + i_1 \Delta d. \tag{20}$$

2) The change in the amount of information that triggers the movement with direct (contact) interaction of objects. When examining this question, the mass of interacting objects will not be looked at, as the change of velocity during direct (contact) interaction depends on the mass and is considered in the calculations provided. Additionally, there is considered a closed system of three objects the mass of which is constant.

a) Assuming there is object R …

- … moving in direction Z with velocity V_R (13)

$$\boldsymbol{V}_R = \frac{d_R}{i_R}\boldsymbol{c},$$

where $\boldsymbol{V}_R$ is the drift velocity of object R in direction Z until collision; d_R is the amount of information that triggers the movement of object R in direction Z until collision; i_R is awareness of object R about movement until collision;

- … will collide with object X and its velocity will become V_{RX}. The change of the amount of information that triggers the movement will correspond to the change of velocity. As it follows from Formula (19)

$$\Delta d_{RX} = d_{RX} i_R - d_R i_{RX},$$

where Δd_{RX} is the change of the amount of information that triggers the movement of object R in direction Z after collision with object X; i_{RX} is awareness of object R about movement after collision with object X; d_{RX} —the amount of information that triggers the movementof object R in direction Z after collision with object X;

- … will collide with object Y and its velocity will become V_{RY}. The change of determination will correspond to the change of velocity. As it follows from Formula (19)

$$\Delta d_{RY} = d_{RY} i_R - d_R i_{RY},$$

where Δd_{RY} is the change of the amount of information that triggers the movement of object R in direction Z after collision with object Y; i_{RY} is awareness of object R about movement after collision with object Y; d_{RY}—the amount of information that triggers the movementof object R in direction Z after collision with object Y;

- … will collide with both objects X and Y and its velocity will become V_{RXY}. From the Formula (19) there follows a new amount of information that triggers the movement

$$\Delta d_{RXY} = d_{RXY} i_R - d_R i_{RXY}, \tag{21}$$

where Δd_{RXY}—is the change of the amount of information that triggers the movementof object R in direction Z after collision with objects X and Y; i_{RXY}—is awareness of object R about movement after collision with object X and Y; d_{RXY}—the amount of information that triggers the movementof object R in direction Z after collision with objects X and Y.

b) Out of information-probabilistic interpretation of the law of conservation of momentum (18) it follows that if two objects interact, the total value of the change of momentum of these objects should equal 0. Only in this case the total momentum does not change. Hence, it can be written

$$\begin{aligned} &\Delta d_{RX} + \Delta d_{XR} = 0; \\ &\Delta d_{RY} + \Delta d_{YR} = 0, \end{aligned} \tag{22}$$

where Δd_{XR} is the change of the amount of information that triggers the movement of object X in direction Z after colliding with object R; d_{YR} is the change of the amount of information that triggers the movementof object Y in direction Z after colliding with object R.

Then, for the case of collision of object R with objects X and Y; taking into account (18), it can be written as

$$\Delta d_{RXY} + \Delta d_{XR} + \Delta d_{YR} = 0.$$

Using (22), it can be obtained:

$$\Delta d_{RXY} = -\Delta d_{XR} - \Delta d_{YR} = \Delta d_{RX} + \Delta d_{RY}. \tag{23}$$

From (20) it follows

$$d_{RXY} = d_R \Delta i_{RXY} + i_R \Delta d_{RXY}, \tag{24}$$

where Δi_{XRY} is the change of awareness of object R about the movement after collision with objects X and Y.

From (9) it follows

$$i_{XRY} = \sqrt{d_{XRY}^2 + 1},$$

where i_{XRY} is awareness of object R about the movement after collision with objects X and Y.

c) New probability of shift of object R in direction Z (12)

$$p_{XRY} = 0.5 + \frac{d_{XRY}}{2 \cdot i_{XRY}}, \quad (25)$$

where p_{XRY} is the probability of shift of object R in direction Z after colliding with objects X and Y.

If the presented model of transformation of probabilistic movement is really implemented in mechanical movement, its formulae may depict some general-laws of our Nature. What if the same formulae are used to transform the information in a human brain? What if they are generally valid? It is the answer to this question that should be found in experiments. To do this, let us first simplify the information-probabilistic interpretation of mechanical movement to the form which makes it possible to solve other problems connected to the existence of on-force interaction.

2.3. Non-Force Interaction Method

The non-force interaction method (NFIM) allows to move from the operation "the amount of information that triggers the movement (mechanical)" to the operation of the amount of information that triggers the reaction (manifestation) (in social, biological or "technical" form of motion of matter).

In the subject field, there are objects that react to non-force influence. There are objects and processes that influence this reaction. The reaction itself can influence the reaction of objects. For instance, the result of a football match is influenced by referees, players, the field condition, audience, etc. However, the result of previous matches also influences the result (through the psychology of players).

The steps of the method:

1) The calculation of the amount of information that triggers the reaction of objects of subject field when non-force influences are absent

$$\forall R_i \in R, \exists r_{ij} \in R_j,$$

where r_{ij} is the possible reactions of object R_i; R_i is the object; R is the multitude of objects of subject field.

$$0 < p(r_{ij}) < 1, \sum_j p(r_{ij}) = 1,$$

where $p(r_{ij})$ is the unconditional probability of reaction r_{ij}.

Out of (11) it follows:

$$d(r_{ij}) = \begin{cases} 0.5 \cdot \sqrt{\dfrac{p(r_{ij})}{1-p(r_{ij})} + \dfrac{1-p(r_{ij})}{p(r_{ij})} - 2}, & p(r_{ij}) \geq 0.5 \\ -0.5 \cdot \sqrt{\dfrac{p(r_{ij})}{1-p(r_{ij})} + \dfrac{1-p(r_{ij})}{p(r_{ij})} - 2}, & p(r_{ij}) < 0.5 \end{cases}$$

where $d(r_{ij})$ is the amount of information that triggers the reaction r_{ij}.

Out of (8) it follows:

$$i\left(r_{ij}\right)=\frac{1}{2\sqrt{p\left(r_{ij}\right)\cdot\left(1-p\left(r_{ij}\right)\right)}},$$

where $i\left(r_{ij}\right)$ is the awareness about the reaction r_{ij}.

2) The calculation of determination and awareness of reactions of objects of subject field to which the non-force influences are applied

$$\forall w_k \in W, \exists R_i \in R, r_{ij} \in R_i : p\left(r_{ij}/w_k\right) \neq p\left(r_{ij}\right),$$

where w_k are influences; $p\left(r_{ij}/w_k\right)$ is conditional probability of reaction r_{ij} if to the object R_i influence w_k is applied.

Out of (11) it follows:

$$\forall w_k \in W, \forall R_i \in R, \forall r_{ij} \in R_i :$$

$$d\left(r_{ij}/w_k\right)=\begin{cases}0.5\cdot\sqrt{\dfrac{p\left(r_{ij}/w_k\right)}{1-p(r_{ij}/w_k)}+\dfrac{1-p\left(r_{ij}/w_k\right)}{p\left(r_{ij}/w_k\right)}-2}, & p\left(r_{ij}/w_k\right)\geq 0.5\\ -0.5\cdot\sqrt{\dfrac{p\left(r_{ij}/w_k\right)}{1-p\left(r_{ij}/w_k\right)}+\dfrac{1-p\left(r_{ij}/w_k\right)}{p\left(r_{ij}/w_k\right)}-2}, & p\left(r_{ij}/w_k\right)<0.5\end{cases}$$

where $d\left(r_{ij}/w_k\right)$ is the determination of the reaction r_{ij} under the conditional that to the object R_i the influence w_k is applied.

Out of (8) it follows:

$$\forall w_k \in W, \forall R_i \in R, \forall r_{ij} \in R_i : i\left(r_{ij}/w_k\right)=\frac{1}{2\sqrt{p\left(r_{ij}/w_k\right)\cdot\left(1-p\left(r_{ij}/w_k\right)\right)}},$$

where $i\left(r_{ij}/w_k\right)$ is the awareness of the object R_i about the reaction r_{ij} under the condition that to it the influence w_k is applied.

3) The calculation of total non-force influence to the objects from (19) and (23)

$$\forall w_k \in W, \forall R_i \in R, \forall r_{ij} \in R_i : \Delta d\left(r_{ij}/W\right)=\sum_{w_k} d\left(r_{ij}/w_k\right)\cdot i\left(r_{ij}\right)-d\left(r_{ij}\right)\cdot i\left(r_{ij}/w_k\right),$$

where $\Delta d\left(r_{ij}/W\right)$ is the value of non-force influence on the reaction r_{ij} of object R_i that equals to the change in the amount of information that triggers the reaction.

Additional awareness that equals to non-force influences (9)

$$\forall w_k \in W, \forall R_i \in R, \forall r_{ij} \in R_i : \Delta i\left(r_{ij}/W\right)=\sqrt{\left(\Delta d\left(r_{ij}/W\right)\right)^2+1},$$

where $\Delta i\left(r_{ij}/W\right)$ is additional awareness about non-force influence on the reaction r_{ij} of object R_i that corresponds to additional non-force influence.

4) The calculation of a new (after influences) amount of information that triggers the reaction of objects of subject field (24)

$$\forall R_i \in R, \forall r_{ij} \in R_i : d\left(r_{ij}/W\right)=\Delta d\left(r_{ij}/W\right)\cdot i\left(r_{ij}\right)+d\left(r_{ij}\right)\cdot\Delta i\left(r_{ij}/W\right), \quad (26)$$

where $d\left(r_{ij}/W\right)$ is a new (after all influence) amount of information that triggers the reaction r_{ij} of object R_i.

Additional awareness that corresponds to new amount of information that triggers the reaction (9)

$$\forall R_i \in R, \forall r_{ij} \in R_i : i\left(r_{ij}/W\right) = \sqrt{\left(d\left(r_{ij}/W\right)\right)^2 + 1},$$

where $i\left(r_{ij}/W\right)$ is new (after all influences) awareness about the reaction r_{ij} of object R_i.

5) The estimate of combined conditional probability of reactions of objects of subject field (12)

$$\forall R_i \in R, \forall r_{ij} \in R_i : \hat{p}\left(r_{ij}/W\right) = 0.5 + \frac{d\left(r_{ij}/W\right)}{2 \cdot i\left(r_{ij}/W\right)},$$

where $\hat{p}\left(r_{ij}/W\right)$ is the estimate of combined conditional probability of reaction r_{ij} after all influences.

The initial data of the method are unconditional and individual conditional probabilities of reactions of objects to non-force influences. The resulting data are the estimate of combined conditional probability of reactions. Therefore, the question arises. Why the estimate and not the probability itself? Considering that out of information-probabilistic interpretation of mechanical movement it follows that the result of calculation is the probability of the shift of objects itself. However, in this case the scheme of calculations for any stochastic subject fields is proposed. Thus, these fields can be characterized by such connection between objects and processes when their combinations can have synergetic effect.

Hence, it refers to the estimate of combined conditional probability of reactions and not to the probability itself.

3. Related Works

Wernicke's and Broca's areas are responsible for the speech processes in a human brain. Wernicke's area, which is also called Wernicke's speech area, is one of the two parts of cerebral cortex connected to speech, the other is Broca's area. Wernicke's area takes part in processing written and spoken language in contrast to Broca's area, which is responsible for speech production [9].

Wernicke's area supports an important component of speech production which is called phonological search where phonemes subject to articulation and their time order are represented mentally. This process is necessary for all the tasks of speech production including repetition, search of words (for instance, during spontaneous speaking or naming) and reading aloud. Repetition of language means entering the system of phonological search through the system of auditory comprehension of phonemes. Similar mechanism supports reading aloud, except the fact that the entrance to the system of phonological search is through the system of visual perception of letters in ventral occipitotemporal area. The production of communicative speech includes the step of phonological search, during which the concept depicting what the speaker wants to say is received. Then the search of words is made through the reflection of these meanings of words in phonological representations. Thus, in contrast to repetition or reading, entrance to the system of phonological search in these tasks is made through internal semantic system (the meaning of word). This semantic processing network is widely-spread in the cortexes of associations of higher level in temporal, parietal and frontal lobes. The processing of language provides the reflection of the sequences of phonemes (they are perceived in the system of perception of auditory phoneme) in the meanings on words (represented in the semantic system) [10].

Today the researches of the speech production processes are mainly dedicated to the determination of neurobiological features of information interaction in a human brain. For instance, in the work "The Brain Basis of Language Processing: From Structure to Function" [11] the structural and functional neural system that is the basis of sentence processing and how this process evolves with time when the sentence is perceived is described. The authors conduct the overview of short outline of timeline of different subprocesses that constitute the process of sentence processing. Then, the general networking function of speech, which is in the brain cortex, and its neuroanatomical architecture are determined. On the basis of this there were described different processes that happen during processing, such as acoustic and phonological analysis as well as syntax and semantic processes. Also, authors [12] [13] argued that speech production includes sensory systems in posterior upper temporal lobe of the left hemisphere and that the interface between perception and movement systems are supported by sensorimotor circuit for the actions of voice routes that is really similar to sensorimotor systems found in the parietal part of primates, and that verbal short-term memory can be understood as integral feature of this sensorimotor circle.

From the position of simulating of speech production processes in a human brain with the aid of mathematical apparatus and computer technologies, nowadays most of the researches are aimed at speech synthesis [14]. The technology of speech synthesis has become the centre of researches in the sphere of intelligent computer. For almost 50 years, the studying of speech synthesis has had considerable development as an interdisciplinary approach [15]. The example of speech synthesis research is the work [16] where there are described concepts of automatic formation of personal digital template of voice to solve the following issues on its basis: computer speech synthesis, continuous speech recognition and identification of a person by voice (three main branches of language technologies). As well as that there is an article [17] where the authors implement and compare the models of identification of spoken language on the basis of deep learning. The authors also use two most modern and popular methods of speech recognition, such as Wav2Vec and SpecAugment, in their classifiers and verify if they are also used in the sphere of speech identification. Among the models that are implemented by authors the classifier of the deep data networks on the basis of X-vector is given the highest rank F1 - 0.91 where target set is composed of five languages. SpecAugment data augmentation method, as it happens, improves the accuracy of classification when it is applied to input mel-spectrograms of CRNN architecture. Even though they receive the accuracy of classification lower than some other methods, Wav2Vec linguistic representations also provide rather promising results.

The researches provided give the answer to the questions how the brain works when it forms or processes the speech. However, despite the considerable number of researches dedicated to the problems of speech production and processing in a human brain, in the process of analysis of modern scientific works not detected were the works that could give the answer to a more important question: why the brain works in this way in the first place? What information laws are in the basis of brain development and structures? How do they function in the process of speech production and processing? If the underlying hypothesis of the NFIT is correct, then in both mechanical movement and the process in a human brain the same laws of non-force (information) interaction should be manifested. Thus, the formulae received from the information-probabilistic interpretation of the mechanical movement should also reflect the processes that are present in a human brain including the ones during speech production and processing. Moreover, in the studied works the correspondence of the existing formulae to the information processes in a human brain connected to speech was not verified, hence the hypothesis of the present research is neither confirmed nor refuted, therefore it requires experimental verification.

4. Hypothesis and Objective of Experimental Research

The hypothesis of research: The hypothetical model of non-force interaction created out of the laws of mechanical movement corresponds to the informational processes in a human brain, connected to speech. This is the indication of the laws' general validity.

Scientific objective of the experiment: is to prove the general validity of the non-force interaction formulae through demonstrating the applicability of the formulae received from information-probabilistic interpretation of mechanical movement in relation to the processes of speech production in a human brain.

The practical objective of the experiment: is to demonstrate the effectiveness of the method of non-force interaction in relation to the processing of natural language texts, which allows to create scientific-practical tools in the form of methods and algorithms of creation of the artificial intelligence systems that can develop reflexes to non-force influences in the functional environment.

Language is the manifestation of informational processed in a human brain. The idea of experiments is to show through the language that informational processes in a human brain run according to the formulae received in the non-force interaction theory. In fact, the objective of the experiments is to demonstrate the fact that the formulae obtained out of the physical laws "work" at the level of human intellectual activity as well. Particularly, in language. In the experiments it will be checked if it is possible to evaluate combined conditional probability by individual conditional probabilities and unconditional probability of text fragment sequence. Mathematically p (O/XY) needs to be evaluated by p (O), p (O/X), p (O/Y). As it is provided in Subsection 2.3 applied to natural language texts.

Such formulation of the problem has also practical value, and in essence it reflects the mechanism of reacting to events (reflexes) of living creatures. In the process of life, each living creature learns how to react to fluences so that ensure its own life-sustaining activity in the best possible way. There is a rule in the core of the reflexes, which says that if X happened, action A is needed. Whereas if Y happened, action B is needed. What is both X and Y happened? In this case, the ability to evaluate combined conditional probability by individual ones can be useful.

If numerical values of speech creation correspond to the formulae received in the theory of non-force interaction, it will mean that intellectual apparatus of a human also uses them when producing speech (and maybe not only speech). In its turn, it means that they most probably are generally valid for the interaction processes in the Nature. Therefore, they can be used to create artificial intelligence systems as well. Is this true? Let us first conduct the experiments, and then look for the answer to this question.

5. Methodology of Experimental Research

All information on experiments is in the database [18].

There are natural language texts in different languages selected. They are the works of William Shakespeare [19] ("English" base), the epic novel of Lev Tolstoy "War and Peace) [20] [21] [22] [23] ("Russian" base), the works of Friedrich Nietzsche, Johann Wolfgang Goethe and Franz Kafka [24] [25] [26] ("German" base) and the works of Ukrainian poets [27] [28] [[29] ("Ukrainian" base).

1) In every sentence, all symbols are rejected except the letters of the corresponding alphabet (the fragments of the such texts are provided in **Figure 2**).

"Russian" Base ***2165328 letters***	***"English" Base*** ***3784551 letters***	***"German" Base*** ***1062279 letters***	***"Ukrainian" Base*** ***531926 letters***
сейчасприбавилаонаопя тьуспокоиваясьнынчеум енядваоченьинтересные человекакстативиконтм ортемаронвродствесмон морансичрезрогановодн аизлучшихфамилийфра нцииэтоодинизхороших эмигрантовизнастоящих ипотомаббатмориовызн аетеэтотглубокийумонб ылпринятгосударемвыз наете	fromfairestcreatureswedesirein creasethattherebybeautysrosem ightneverdiebutastheripershoul dbytimedeceasehistenderheirm ightbearhismemorybutthoucon tractedtothineownbrighteyesfe edstthylightsflamewithselfsubs tantialfuelmakingafaminewher eabundanceliesthyselfthyfoetot hysweetselftoocruelthouthatart nowtheworldsfreshornamentan donlyheraldtothegaudyspringw ithinthineownbudburiestthycon tentandtenderchurlmakstwastei nniggardingpitytheworldorelse thisgluttonbetoeattheworldsdu ebythegraveandthee	gleicheineraltenhalbv erklungnensagekom mtersteliebundfreund schaftmitheraufdersc hmerzwirdneueswied erholtdieklagedesleb enslabyrinthischirren lauf	огожсиротинакогозап итаєіхтоїйрозкажеіхт отеєзнаєдемилийноч уєчивтемномугаючив бистрімдунаюконяна повачиможездругоюд ругуюкохаєїїчорнобр ивуужезабува

Figure 2. The fragments of texts prepared for experiments.

2) Each sentence is divided into consecutive letter combinations (fragments) with the length of L letters ($L = 1$, $L = 2$).

3) The statistical probability of the order of each fragment is calculated, as well as the probability of appearance of a fragment between two other fragments. For the text: $a_1, a_2, \cdots, a_{i-1}, a_i, a_{i+1}, \cdots, a_n$, the probability

$$p(a_i) = \frac{n(a_i)}{N_1},$$

where $n(a_i)$ is the number of times fragment a_i appears between other fragments in the text sentences; N_1 is the total number of fragment combinations present in the sentences of a text; $p(a_i)$ is the statistic unconditional probability of the sequence of text fragment a_i.

$$p(a_i/a_{i-1}a_{i+1}) = \frac{n(a_{i-1}, a_i, a_{i+1})}{n(a_{i-1}, a_{i+1})},$$

where $n(a_{i-1}, a_i, a_{i+1})$ is the number of times a fragment combination a_{i-1}, a_i, a_{i+1} appears in the sentences of a text; $n(a_{i-1}, a_{i+1})$ is the number of times fragment combination $a_{i-1}, \cdots, a_{i+1}$ appears in the sentences of a text; $p(a_i/a_{i-1}a_{i+1})$ is the statistical unconditional probability of the sequence of text fragment a_i if the previous text fragment is a_{i-1}, and the following is a_{i+1}.

4) The statistical probability of sequence of each fragment after another fragment is calculated:

$$p(a_i/a_{i-1}) = \frac{n(a_{i-1}, a_i)}{n(a_{i-1})},$$

where $n(a_{i-1}, a_i)$ is the number of times fragment combination $a_{i-1}, a_i, \cdots$ appears in the sentences of a text; $n(a_{i-1})$ is the number of times a fragment $a_{i-1}, \cdots$ appears in the sentences of a text; $p(a_i/a_{i-1})$ is the statistic conditional probability of sequence of the text fragment a_i if the previous text fragment is a_{i-1}.

5) The statistical probability of sequence of each fragment before another fragment is calculated:

$$p(a_i/a_{i+1}) = \frac{n(a_i, a_{i+1})}{n(a_{i+1})},$$

where $n(a_i, a_{i+1})$ is the number of times the combination of fragments $\cdots, a_i, a_{i+1}$ appears in the sentences of a text; $n(a_{i+1})$ is the number of times fragment $\cdots, a_{i+1}$ appears in the sentences of a text; $p(a_i/a_{i+1})$ is the statistical conditional probability of sequence of text fragment a_i if the next fragment is a_{i+1}.

6) B All the combinations of fragments for which $(a_{i-1}, a_i) > 0$ or $n(a_i, a_{i+1}) > 0$ (even if $n(a_{i-1}, a_i, a_{i+1}) = 0$) are recorded in the database.

7) Methods M$_s$ of determination of combined conditional probability are chosen. The value received by such methods will be called estimate of sequence of the text fragments.

$$p_s(a_i/a_{i-1}a_{i+1}),$$

where $p_s(a_i/a_{i-1}a_{i+1})$ is the estimate of combined conditional probability of sequence of text fragment a_i by method M_s; *s* the number of a method.

8) The estimate of combined conditional probability is calculated by using the chosen methods M_s.

9) The chosen methods are assessed by the deviation of the estimates of combined conditional probability of sequence of text fragment a_i by method M_s from the conditional probabilities themselves.

10) The results are analysed. If the results are received by the method of non-force interaction are found to be better, it can be stated that the objective of the experiments is achieved.

6. Experimental Methods

For each combination of fragments, the combined conditional probability estimate is calculated by 9 different methods:

1) By unconditional probability:

$$p_1(a_i/a_{i-1}a_{i+1}) = p(a_i),$$

where $p_1(a_i/a_{i-1}a_{i+1})$ is the estimate of combined conditional probability of sequence of text fragment a_i by its unconditional probability.

2) By conditional probability of the previous fragment:

$$p_2(a_i/a_{i-1}a_{i+1}) = p(a_i/a_{i-1}),$$

where $p_2(a_i/a_{i-1}a_{i+1})$ is the estimate of combined conditional probability of sequence of text fragment a_i by conditional probability of its appearance if the previous text fragment is a_{i-1}.

3) By conditional probability of the following fragment:

$$p_3(a_i/a_{i-1}a_{i+1}) = p(a_i/a_{i+1}),$$

where $p_3(a_i/a_{i-1}a_{i+1})$ is the estimate of combined conditional probability of sequence of text fragment a_i by conditional probability of its appearance if the following text fragment is a_{i+1}.

4) By the average value of individual conditional probabilities:

$$p_4(a_i/a_{i-1}a_{i+1}) = \frac{p(a_i/a_{i-1}) + p(a_i/a_{i+1})}{2},$$

where $p_4(a_i/a_{i-1}a_{i+1})$ is the estimate of combined conditional probability of sequence of text fragment a_i by the average value of conditional probabilities of its appearance if the previous text fragment is a_{i-1} and the following text fragment is a_{i+1}.

5) By weighted sum of individual conditional probabilities (the approximation by linear function using the method of least squares) (hereinafter, Method 1)

$$p_5(a_i/a_{i-1}a_{i+1}) = \alpha_1 \cdot p(a_i/a_{i-1}) + \alpha_2 \cdot p(a_i/a_{i+1}) + \alpha_3, \tag{27}$$

under the condition that

$$\sum_{a_i, a_{i-1}, a_{i+1}} \left(p_5(a_i/a_{i-1}a_{i+1}) - p(a_i/a_{i-1}a_{i+1})\right)^2 \to \min, \tag{28}$$

where $p_5(a_i/a_{i-1}a_{i+1})$ is the estimate of combined conditional probability of sequence of text fragment a_i by linear approximation of conditional probabilities of its appearance: if the previous text fragment is a_{i-1}; the following text fragment is a_{i+1}; $\alpha_1, \alpha_2, \alpha_3$ are approximation coefficients.

6) Taking into account the values of individual conditional probabilities (hereinafter, Method 2). Also, the approximation by linear function with minimizing of deviation is done:

$$\begin{aligned} p_6(a_i/a_{i-1}a_{i+1}) = \beta_1 \cdot \max\left(p(a_i/a_{i-1}), p(a_i/a_{i+1})\right) \\ + \beta_2 \cdot \min\left(p(a_i/a_{i-1}), p(a_i/a_{i+1})\right) + \beta_3, \end{aligned} \tag{29}$$

under the condition that

$$\sum_{a_i, a_{i-1}, a_{i+1}} \left(p_6(a_i/a_{i-1}a_{i+1}) - p(a_i/a_{i-1}a_{i+1})\right)^2 \to \min, \tag{30}$$

where $p_6(a_i/a_{i-1}a_{i+1})$ is the estimate of conditional probability of sequence of text fragment a_i comparing to the values of individual conditional probabilities: if the previous text fragment is a_{i-1}; the following text fragment is a_{i+1}; $\beta_1, \beta_2, \beta_3$ are approximation coefficients.

7) Taking into account the deviation of the second conditional probability from unconditional (hereinafter, Method 3):

$$p_7(a_i/a_{i-1}a_{i+1}) = \gamma_1 \cdot p(a_i/a_{i-1}) + \gamma_2 \cdot \left(p(a_i/a_{i+1}) - p(a_i)\right) + \gamma_3, \tag{31}$$

under the condition that

$$\sum_{a_i, a_{i-1}, a_{i+1}} \left(p_7(a_i/a_{i-1}a_{i+1}) - p(a_i/a_{i-1}a_{i+1})\right)^2 \to \min, \tag{32}$$

where $p_7(a_i/a_{i-1}a_{i+1})$ is the estimate of conditional probability of sequence of text fragment a_i by linear approximation of deviation of the second conditional probability from unconditional: if the previous text fragment is a_{i-1}; the following text fragment is a_{i+1}; γ_1, γ_2 are approximation coefficients.

8) Taking into account the deviation of smaller conditional probability from unconditional (hereinafter Method 4). Let us assume that $p_i^{\max}$ is maximum. Accordingly, $p_i^{\min}$ is the smallest of these two values. Then,

$$p_8(a_i/a_{i-1}a_{i+1}) = \delta_1 \cdot p_i^{\max} + \delta_2 \cdot \left(p_i^{\min} - p(a_i)\right) + \delta_3, \tag{33}$$

under the condition that

$$\sum_{a_i, a_{i-1}, a_{i+1}} \left(p_8(a_i/a_{i-1}a_{i+1}) - p(a_i/a_{i-1}a_{i+1})\right)^2 \to \min, \tag{34}$$

where $p_8(a_i/a_{i-1}a_{i+1})$ is the estimate of conditional probability of text fragment a_i sequence by linear approximation of deviation of a small conditional probability from an unconditional one: if the previous text fragment is a_{i-1}; the following text fragment is a_{i+1}; δ_1, δ_2 are approximation coefficients.

It is possible to invent the multitude of heuristic methods of calculating the estimate of combined conditional probability, not only the ones presented in pp. 5-8. The theory of non-force interaction started from the search of such heuristics that could give the best result when processing natural language texts (the experiments were conducted with the aim to create the system of natural speech access to databases in the basis of which was not time-consuming process of syntax, morphological, semantic machine analysis of a text, but rather a reaction to the fragments of texts [30]. Thus, when there was chosen heuristics which could provide the best result, the search of the answer to the question: "why it is like this?" has begun. The solution was found through information-probabilistic interpretation of mechanical movement [4] [5].

It is this solution that was put in the basis of the non-force interaction theory.

9) Using the **method of non-force interaction**, proposed in the theory of non-force interaction (see Subsection 2.3). By "reaction" we mean "fragment of text". Regarding the language, in the method the following steps of calculation of non-force influences on the process of text formation and determination of probabilities of sequence of its fragments are implemented:

a) The calculation of the influence size. Let us determine the amount of information that triggers a piece of text (11)

$$0 < p(a_i) < 1;\ 0 < p(a_i/a_{i-1}) < 1;\ 0 < p(a_i/a_{i+1}) < 1:$$

$$d(a_i) = \begin{cases} 0.5 \cdot \sqrt{\dfrac{p(a_i)}{1-p(a_i)} + \dfrac{1-p(a_i)}{p(a_i)} - 2},\ p(a_i) \ge 0.5 \\ -0.5 \cdot \sqrt{\dfrac{p(a_i)}{1-p(a_i)} + \dfrac{1-p(a_i)}{p(a_i)} - 2},\ p(a_i) < 0.5 \end{cases}$$

$$d(a_i/a_{i-1}) = \begin{cases} 0.5 \cdot \sqrt{\dfrac{p(a_i/a_{i-1})}{1-p(a_i/a_{i-1})} + \dfrac{1-p(a_i/a_{i-1})}{p(a_i/a_{i-1})} - 2},\ p(a_i/a_{i-1}) \ge 0.5 \\ -0.5 \cdot \sqrt{\dfrac{p(a_i/a_{i-1})}{1-p(a_i/a_{i-1})} + \dfrac{1-p(a_i/a_{i-1})}{p(a_i/a_{i-1})} - 2},\ p(a_i/a_{i-1}) < 0.5 \end{cases}$$

$$d(a_i/a_{i+1}) = \begin{cases} 0.5 \cdot \sqrt{\dfrac{p(a_i/a_{i+1})}{1-p(a_i/a_{i+1})} + \dfrac{1-p(a_i/a_{i+1})}{p(a_i/a_{i+1})} - 2},\ p(a_i/a_{i+1}) \ge 0.5 \\ -0.5 \cdot \sqrt{\dfrac{p(a_i/a_{i+1})}{1-p(a_i/a_{i+1})} + \dfrac{1-p(a_i/a_{i+1})}{p(a_i/a_{i+1})} - 2},\ p(a_i/a_{i+1}) < 0.5 \end{cases}$$

where $d(a_i)$ is the amount of information that triggers a piece of text a_i; $d(a_i/a_{i-1})$ is the amount of information that triggers a piece of text a_i after fragment a_{i-1}; $d(a_i/a_{i+1})$ is the amount of information that triggers a piece of text a_i before fragment a_{i+1}.

b) Let us calculate the difference in the determination (amount of information) by applying Formula (9) in (19)

$$\Delta d(a_i/a_{i-1}) = d(a_i/a_{i-1}) \cdot \sqrt{d(a_i)^2 + 1} - d(a_i) \cdot \sqrt{d(a_i/a_{i-1})^2 + 1};$$

$$\Delta d(a_i/a_{i+1}) = d(a_i/a_{i+1}) \cdot \sqrt{d(a_i)^2 + 1} - d(a_i) \cdot \sqrt{d(a_i/a_{i+1})^2 + 1},$$

where $\Delta d(a_i/a_{i-1})$ is the size of influence which appears in the process of production of fragment a_{i-1} on the probability of fragment a_i as the following fragment (non-force influence of a human brain on the presence of fragment a_i when creating fragment a_{i-1}); $\Delta d\left(a_i/a_{i+1}\right)$ is the size of influence which appears in the process of production of fragment a_{i+1} on the probability of production of fragment a_i as the previous fragment (the non-force influence of a human brain on the presence of fragment a_i when creating fragment a_{i+1}).

c) The non-force influence on the appearance of text fragment a_i (23):

$$\Delta d\left(a_i/a_{i-1}a_{i+1}\right)=\Delta d\left(a_i/a_{i-1}\right)+\Delta d\left(a_i/a_{i+1}\right),$$

where $\Delta d\left(a_i/a_{i-1}a_{i+1}\right)$ is a combined additional influence that appears in the process of production of fragments a_{i-1} and a_{i+1} and which influences the possibility of fragment a_i being formed next.

d) New determination of the amount of information that triggers a piece of text a_i (from Formulae (9) and (26)):

$$d\left(a_i/a_{i-1}a_{i+1}\right)=d\left(a_i\right)\cdot\sqrt{\left(\Delta d\left(a_i/a_{i-1}a_{i+1}\right)\right)^2+1}+\Delta d\left(a_i/a_{i-1}a_{i+1}\right)\cdot\sqrt{\left(d\left(a_i\right)\right)^2+1},$$

where $d\left(a_i/a_{i-1}a_{i+1}\right)$ is the amount of information that triggers a piece of text a_i taking into account non-force influence.

e) The estimate of probability of fragment a_i presence (after both influences) (12):

$$p_9\left(a_i/a_{i-1}a_{i+1}\right)=0.5+\frac{d\left(a_i/a_{i-1}a_{i+1}\right)}{2\cdot\sqrt{\left(d\left(a_i/a_{i-1}a_{i+1}\right)\right)^2+1}},\tag{35}$$

where $p_9\left(a_i/a_{i-1}a_{i+1}\right)$ is the estimate of conditional probability of text fragment a_i sequence, through non-force influence on the possibility of fragment a_i production, which appears in the process of producing fragments a_{i-1} and a_{i+1}.

7. Methods' Effectiveness Evaluation Criteria

The effectiveness of the methods is to be evaluated by the following criteria:

1) Standard deviation of the estimate of combined conditional probability, received by method M_s from statistical combined conditional probability of text fragment sequence:

$$\sigma_s=\sqrt{\frac{\sum_{i=1}^{N_s}\left(p_s\left(a_i/a_{i-1}a_{i+1}\right)-p\left(a_i/a_{i-1}a_{i+1}\right)\right)^2}{N_s}},\tag{36}$$

where N_s is quantity of text fragments about which the estimate of combined conditional probability is calculated by method M_s; $p_s\left(a_i/a_{i-1}a_{i+1}\right)$ is estimate of combined conditional probability of text fragment sequence calculated by method M_s; $p\left(a_i/a_{i-1}a_{i+1}\right)$ is combined conditional probability of text fragment sequence; σ_s is standard deviation of estimate of combined conditional probability of text fragment sequence received by method M_s from statistical combined conditional probabilities.

The advantage of non-force interaction method over the other will be calculated by dividing the difference between deviation of NFIM and the smallest deviation of other methods by deviation of NFIM and multiplying by 100%:

$$Y_\sigma = \frac{\sigma_9 - \max\limits_{1\le i\le 8} \sigma_i}{\sigma_9} \cdot 100\%, \quad (37)$$

where Y_σ is the advantage of non-force interaction method in standard deviation of estimate of combined conditional probability of text fragment sequence.

2) The percentage of correctly predicted text fragments:

$$\mu_s = \frac{\sum_{a_{i-1}a_{i+1}} \left(n\left(a_i / a_{i-1}a_{i+1}\right) \mid \max_{a_i} \left[p_s\left(a_i / a_{i-1}a_{i+1}\right)\right]\right)}{\sum_{a_{i-1}a_{i+1}} n\left(a_{i-1}a_{i+1}\right)} \cdot 100\%, \quad (38)$$

where μ_m is percentage of correct predictions of text fragment sequence made by M$_s$; $p_s\left(a_i / a_{i-1}a_{i+1}\right)$ is estimate of combined conditional probability of text fragment a_i sequence made by method M$_s$; $n\left(a_i / a_{i-1}a_{i+1}\right)$ is the quantity of letter combinations where the combination of fragments $a_{i-1}a_i a_{i+1}$ is present; $n\left(a_{i-1}a_{i+1}\right)$ is the quantity of letter combinations where the combination of fragments a_{i-1} < any fragment > a_{i+1} is present.

The advantage of non-force interaction method over the others will be calculated by diving the difference between the percentage (quantity) of correctly predicted text fragments, made by NFIM and the biggest percentage (quantity) of text fragments predicted correctly by other methods by percentage (quantity) of text fragments predicted correctly by NFIM and multiplying by 100%:

$$Y_\mu = \frac{\mu_9 - \max\limits_{1\le i\le 8} \mu_i}{\mu_9} \cdot 100\%, \quad (39)$$

where Y_μ is the advantage of non-force interaction method in predicting text fragments appearance.

3) Standard deviation of the rank of estimate of combined conditional probability received by method M_s from the range of nonzero statistical combined conditional probability of text fragment sequence:

$$V_s = \sqrt{\frac{\sum_{i=1}^{N_s} \left(u_s\left(a_i / a_{i-1}a_{i+1}\right) - u\left(a_i / a_{i-1}a_{i+1}\right)\right)^2}{N_s}}, \quad (40)$$

under the condition that

$$p\left(a_i / a_{i-1}a_{i+1}\right) > 0,$$

where V_s is standard deviation of the rank of estimate of combined conditional probability of text fragment sequence from the rank of statistical conditional probability in method M$_s$; $u_s\left(a_i / a_{i-1}a_{i+1}\right)$ is rank of estimate of combined conditional probability of text fragment sequence received by method M$_s$; $p\left(a_i / a_{i-1}a_{i+1}\right)$ is combined conditional probability of text fragment sequence; $u\left(a_i / a_{i-1}a_{i+1}\right)$ is rank of combined conditional probability of text fragment sequence.

As a rank, an ordinate number in the ordered range of probabilities of text fragment sequence is understood. For the sequence:

$$p\left(a_{i_1}/a_{i-1}a_{i+1}\right) > p\left(a_{i_2}/a_{i-1}a_{i+1}\right) > \cdots > p\left(a_{i_f}/a_{i-1}a_{i+1}\right) > \cdots > p\left(a_{i_k}/a_{i-1}a_{i+1}\right),$$

the rank of conditional probabilities will be the following:

$$u\left(a_{i_1}/a_{i-1}a_{i+1}\right) = 1;$$

$$u\left(a_{i_2}/a_{i-1}a_{i+1}\right) = 2;$$

$$\vdots$$

$$u\left(a_{i_f}/a_{i-1}a_{i+1}\right) = f;$$

$$\vdots$$

$$u\left(a_{i_k}/a_{i-1}a_{i+1}\right) = k.$$

For the sequence received by method M_s:

$$p_s\left(a_{j_1}/a_{i-1}a_{i+1}\right) > p_s\left(a_{j_2}/a_{i-1}a_{i+1}\right) > \cdots > p_s\left(a_{j_r}/a_{i-1}a_{i+1}\right) > \cdots > p_s\left(a_{j_k}/a_{i-1}a_{i+1}\right),$$

the rank of estimates of combined conditional probabilities will be the following:

$$u_s\left(a_{j_1}/a_{i-1}a_{i+1}\right) = 1;$$

$$u_s\left(a_{j_2}/a_{i-1}a_{i+1}\right) = 2;$$

$$\vdots$$

$$u_s\left(a_{j_r}/a_{i-1}a_{i+1}\right) = r;$$

$$\vdots$$

$$u_s\left(a_{j_k}/a_{i-1}a_{i+1}\right) = k.$$

This criterion is chosen because the estimate of combined conditional probability received by any method and the probability itself do not coincide. This is caused, in the first place, by the synergetic effect. That is by one more direction of evaluation was chosen **the ranking of probability estimates and probabilities themselves of text fragments.** How each method allows to rank fragments correctly according to the frequency of their appearance in a natural text. As well as the criterion of prediction, this one is really important and often used in artificial intelligence systems.

The advantage of non-force interaction method over the others will be calculated by diving the difference between the deviation of NFIM and the smallest deviation of other methods by the deviation of NFIM and multiplying by 100%:

$$Y_V = \frac{V_9 - \max\limits_{1\le i\le 8} V_i}{V_9} \cdot 100\%, \tag{41}$$

where Y_V is the advantage of non-force interaction method in standard deviation of the rank of estimate of combined conditional probability from the rank of combined conditional probability of text fragment sequence.

Methods provided in pp. 5-8 can form the estimate of combined conditional probability which is more than 1. To eliminate this, the author used the normalizing, which is division by the biggest value of result. However, the experiments showed that in this case the deviation of combined conditional probability estimates from the conditional probability of text fragment sequence itself has increased. In order not to be "blamed" in lowering the results of approximation methods, below there are non-normalized values of approximation methods are compared to non-force interaction method.

As to the criteria of the best prediction and the deviation in ranks, normalizing does not influence the result. Since for predicting the highest estimate is chosen (and normalizing does not change this choice), and ranking decides on the estimate sequence (normalizing does not change it either).

8. Software Tools

To implement the methodology stated in Section 5, there was developed a program "Experiments on NFIT" in VBA Access. It contains the interpreter of the texts (implements pp. 1-2 of Section 5), statistics formation module (pp. 3-5 of Section 5), module to calculate estimates of combined conditional probability by different methods (pp. 6-8 of Section 5), module of results analysis and display (pp. 9-10 of Section 5).

Time spent on conduction of experiments connected with the application of provided methodology to four natural language texts on a desktop computer (PC) is approximately 200 hours. Generalized algorithm of calculation of estimates of combined conditional probabilities of text fragment sequence includes the following points:

1) Transformation of the text into the set of 1- and 2-letter sequenced fragments.

2) Calculation of statistical characteristics of a text (unconditional and conditional probabilities of text fragment sequence).

3) Setting of the parameters of calculation (random or input text, with or without reference to unconditional probability of current text fragment sequence, with division of the text into educating and check samples, merger of texts, etc.)

4) Calculation of coefficients in approximation equations.

5) Calculation of estimates of combined conditional probability by all methods.

6) Evaluation of results and formation of reports.

7) Display of results.

To make the algorithm of calculation more understandable, let us consider the example of calculation of estimates of combined conditional probability by different methods.

9. The Example of Calculation (Fragment of "English" Base)

Let us consider three two-letter fragments: $a_{i-1} = $ "ab"; $a_i = $ "le"; $a_{i+1} = $ "in".

$$p(\text{“le”}) = 0.006458;$$

$$p(\text{“le”}/\text{“ab”}) = 0.233333;$$

$$p(\text{“le”}/\text{“in”}) = 0.002379;$$

$$p(\text{“le”}/\text{“ab”“in”}) - ?$$

For each combination of fragments, the calculation of estimate of combined conditional probability is made by the methods provided above. The results are summarized in **Table 1**. What conclusions can be made:

1) The best method for this combination of fragments if the one based on the results received in the non-force interaction theory.

2) None of the methods gives exact value of combined conditional probability. If the intellectual apparatus of a human had also developed for 13.8 billion years, the regularity in formation of text fragments would exactly correspond to the formulae interpreted from the laws of mechanical movement?!

It is a joke, of course. The peculiarity of human intellectual apparatus is the implementation of synergistic features of a language. The combination of fragments, by contents, is considerably bigger than their total sum! However, the fact that the non-force interaction theory provides the biggest approximation even in this example requires a more serious confirmation, as it is wrong to judge by one fragment. Within the experiment, there were processed the statistics by all fragments in the selected works of writing [19]-[29]. Let is consider the results of the conducted experiments.

10. Results of Experiments

Having set input texts (Section 5) for the developed program (Section 8) and calculated unconditional and conditional probabilities of appearance of fragments (letter combinations) of texts of one- and two-letter length, there were formed statistical tables, in accordance to the chosen criteria (Section 7).

Unconditional statistical probabilities for 1-letter fragments are shown in **Tables 2-5**. For 2-letter fragments such tables contain 941 records (“Russian” base), 609 (“English base”), 956 (“Ukrainian” base), 709 (“German” base).

Let us consider the results received.

Experiment 1. Calculation of approximation coefficients.

For each text, there are determined approximation coefficients that correspond to conditions (28), (30), (32), and (34). Approximation coefficients are stated in **Table 6**. As it can be seen from **Table 6**, these coefficients are different enough for the texts in different languages. This means that it is impossible to find such linear approximation which will be optimal for different texts in different languages.

Experiment 2. Determination of standard deviation of combined conditional probability estimate from statistical combined conditional probability of text fragment sequence.

<u>Evaluation criterion: standard deviation (36).</u>

Table 1. Results of estimating of combined conditional probability of appearance of fragment "le" with neighbouring fragments "ab" and "in" in "English" base made by different methods.

№	Name of method	Formula	Value	Difference from actual value 0.192308	Difference rank
1.	By unconditional probability	$p(\text{“le”})$	0.006458	−0.18585	8
2.	By conditional probability of a previous fragment	$p(\text{“le”/“ab”})$	0.233333	0.041025	5
3.	By conditional probability of a following fragment	$p(\text{“le”/“in”})$	0.002379	−0.189929	9
4.	By mean probability	$\frac{p(\text{“le”/“ab”})+p(\text{“le”/“in”})}{2}$	0.117856	−0.07445	7
5.	Method 1. Coefficients: $\alpha_1=0.664$; $\alpha_2=0.714$; $\alpha_3=-0.001$.	$\alpha_1\cdot p(\text{“le”/“ab”})+\alpha_2\cdot p(\text{“le”/“in”})+\alpha_3$	0.155632	−0.03668	4
6.	Method 2. Coefficients: $\beta_1=0.484$; $\beta_2=3.562$; $\beta_3=-0.002$.	$\beta_1\cdot p(\text{“le”/“ab”})+\beta_2\cdot p(\text{“le”/“in”})+\beta_3$	0.119407	−0.0729	6
7.	Method 3. Coefficient: $\gamma_1=0.707$; $\gamma_2=0.743$; $\gamma_3=0.001$.	$\gamma_1\cdot p(\text{“le”/“ab”})+\gamma_2\cdot\left(p(\text{“le”/“in”})-p(\text{le})\right)+\gamma_3$	0.167734	−0.02457	3
8.	Method 4. Coefficient: $\delta_1=0.682$; $\delta_2=1.990$; $\delta_3=0.004$.	$\delta_1\cdot p(\text{“le”/“ab”})+\delta_2\cdot\left(p(\text{“le”/“in”})-p(\text{le})\right)+\delta_3$	0.167867	−0.02444	2
9.	**Non-force interaction method**			**−0.01171**	**1**
	a) Calculation of influence size				
	$d(\text{“le”})$		−6.161437		
	$\Delta d(\text{“le”/“ab”})$		3.348290		
	$\Delta d(\text{“le”/“in”})$		−0.522639		
	b) Combined additional influence $\Delta d(\text{“le”/“ab”“in”})$	$\Delta d(\text{“le”/“ab”})+\Delta d(\text{“le”/“in”})$	2.825651		
	c) New quantity of information about the presence of fragment "le" $d(\text{“le”/“ab”“in”})$	$d(\text{“le”})\cdot\sqrt{\left(\Delta d(\text{“le”/“ab”“in”})\right)^2+1}+\Delta d(\text{“le”/“ab”“in”})\cdot\sqrt{\left(d(\text{“le”})\right)^2+1}$	−0.830304		
	d) Estimate of probability of fragment a_i presence (after both influences).	$0.5+\frac{d(\text{“le”/“ab”“in”})}{2\cdot\sqrt{\left(d(\text{“le”/“ab”“in”})\right)^2+1}}$	**0.180596**		

Table 2. Frequency of appearance of Russian alphabet letters in "Russian" base.

Fragment	Frequency	Probability
а	175,827	0.083292
б	37,245	0.017644
в	98,741	0.046775
г	42,105	0.019946
д	65,559	0.031056
е	176,940	0.083819
ж	23,074	0.010931
з	37,060	0.017556
и	145,085	0.068729
й	23,616	0.011187
к	71,762	0.033995
л	108,142	0.051229
м	63,055	0.029870
н	138,196	0.065466
о	248,121	0.117539
п	56,211	0.026628
р	95,332	0.045160
с	114,635	0.054304
т	125,962	0.059670
у	57,720	0.027343
ф	4385	0.002077
х	18,300	0.008669
ц	7694	0.003645
ш	20,128	0.009535
щ	6390	0.003027
ъ	923	0.000437
ы	41,442	0.019632
ь	41,546	0.019681
э	6409	0.003036
ю	12,849	0.006087
я	46,515	0.022035

Table 3. Frequency of Latin letter appearance in "English" base.

Fragment	Frequency	Probability
a	284,554	0.07714
b	58,963	0.015984

Continued

c	84,602	0.022935
d	143,045	0.038778
e	433,237	0.117446
f	77,559	0.021025
g	65,513	0.01776
h	233,002	0.063164
i	250,734	0.067971
j	4347	0.001178
k	32,997	0.008945
l	165,938	0.044984
m	107,653	0.029184
n	238,352	0.064615
o	311,075	0.084329
p	54,977	0.014904
q	3090	0.000838
r	232,522	0.063034
s	238,711	0.064712
t	319,496	0.086612
u	127,585	0.034587
v	36,926	0.01001
w	86,719	0.023509
x	5223	0.001416
y	90,381	0.024501
z	1616	0.000438

Table 4. Frequency of appearance of German alphabet letters in "German" base.

Fragment	Frequency	Probability
a	49,004	0.050259
ä	4965	0.005092
b	17,785	0.018241
c	36,940	0.037886
d	44,264	0.045398
e	149,403	0.15323
f	17,020	0.017456
g	30,778	0.031566

Continued

h	61,621	0.063199
i	76,184	0.078135
j	2546	0.002611
k	11,361	0.011652
l	39,694	0.040711
m	27,415	0.028117
n	92,783	0.09516
o	26,590	0.027271
ö	3229	0.003312
p	7638	0.007834
q	283	0.00029
r	65,295	0.066968
s	64,256	0.065902
ß	3486	0.003575
t	60,144	0.061685
u	37,803	0.038771
ü	6380	0.006543
v	7429	0.007619

Table 5. Frequency of appearance of Ukrainian alphabet letters in "Ukrainian" base.

Fragment	Frequency	Probability
а	35,710	0.09545
б	7862	0.02101
в	16,595	0.04436
г	6644	0.01776
д	12,866	0.03439
е	20,693	0.05531
є	2333	0.00624
ж	3885	0.01038
з	7913	0.02115
и	25,255	0.06750
і	15,511	0.04146
ї	1914	0.00512

Continued

й	6100	0.01630
к	12,404	0.03315
л	17,528	0.04685
м	12,277	0.03281
н	20,282	0.05421
о	36,527	0.09763
п	9957	0.02661
р	15,599	0.04169
с	16,822	0.04496
т	21,300	0.05693
у	12,561	0.03357
ф	120	0.00032
х	4285	0.01145
ц	1831	0.00489
ч	5345	0.01429
ш	2862	0.00765
щ	1806	0.00483
ь	6855	0.01832
ю	4348	0.01162
я	8146	0.02177

Processing of texts by the program “Experiments by NFIT” allowed to receive the integral values of deviation of calculated combined conditional probability estimates (36) (**Table 7**). As it can be seen from **Table 7**, non-force interaction method gives smaller deviation of probability estimate from its statistical value than other methods in all the texts except “Russian” base (one-letter fragments).

Having applied Fisher distribution to values stated in **Table 7**, it is received a confirmation of statistical hypotheses about exceedance of variance of other methods over the variance of non-force interaction method [31] (excluding Russian text with singular length of fragments) with significance level of $\alpha = 0.01$ (**Table 8**). In **Table 8**, for comparison it is considered the deviation variance of combined conditional probability estimate from combined conditional probability itself received by NFIM and the smallest deviation variance of combined conditional probability estimate from combined conditional probability itself received by other methods. The confirmation of these hypotheses indicates that for other methods (which have a bigger deviation with the same degrees of freedom) they will be confirmed too.

Table 6. Coefficients in approximation methods that provide the minimum standard deviation of combined conditional probability estimate from combined conditional probability of text fragment sequence (fulfilment of conditions of Formulas (28), (30), (32) and (34)).

Base	L	Method 1			Method 2			Method 3			Method 4		
		α_1	α_2	α_3	β_1	β_2	β_3	χ_1	χ_2	χ_3	δ_1	δ_2	δ_3
"Russian"	1	0.613	0.588	−0.006	0.292	1.592	−0.005	0.741	0.669	0.008	0.663	1.085	0.018
	2	0.663	0.673	−0.001	0.472	4.293	−0.002	0.692	0.689	0.000	0.644	2.367	0.004
"German"	1	0.785	0.527	−0.011	0.529	1.130	−0.011	0.915	0.684	0.003	0.815	1.006	0.010
	2	0.723	0.708	−0.002	0.496	3.017	−0.002	0.777	0.760	0.000	0.720	1.948	0.003
"Ukrainian"	1	0.720	0.618	−0.011	0.374	1.419	−0.007	0.857	0.786	0.004	0.746	1.226	0.016
	2	0.782	0.813	−0.002	0.498	4.516	−0.002	0.829	0.851	0.000	0.741	3.074	0.004
"English"	1	0.769	0.600	−0.014	0.521	1.186	−0.015	0.914	0.715	0.003	0.809	1.040	0.012
	2	0.664	0.714	−0.001	0.484	3.562	−0.002	0.707	0.743	0.001	0.682	1.990	0.004

Table 7. Standard deviation of combined conditional probability estimates from statistical combined conditional probability of text fragment sequence.

Base	L	By unconditional probability	By 1st fragment	By 2nd fragment	By mean probability	Method 1	Method 2	Method 3	Method 4	**NFIM**	Advantage of NFIM (%) (37)
"Russian"	1	0.09457	0.08879	0.09018	0.08228	0.08170	**0.07842**	0.08182	0.08117	0.08090	−3.05
	2	0.04313	0.04236	0.04227	0.04121	0.04107	0.04028	0.04106	0.04073	**0.03951**	1.96
"German"	1	0.10891	0.09320	0.10388	0.08973	0.08714	0.08690	0.08559	0.08596	**0.08142**	5.12
	2	0.05479	0.05296	0.05322	0.05148	0.05110	0.05019	0.05102	0.05058	**0.04839**	3.71
"Ukrainian"	1	0.08289	0.07339	0.07588	0.06849	0.06694	0.06486	0.06544	0.06455	**0.06204**	4.06
	2	0.04803	0.04731	0.04715	0.04662	0.04637	0.04561	0.04634	0.04589	**0.04491**	1.56
"English"	1	0.10037	0.08645	0.09298	0.08129	0.07845	0.07769	0.07768	0.07787	**0.07466**	4.05
	2	0.04393	0.04292	0.04265	0.04149	0.04127	0.04049	0.04124	0.04092	**0.03948**	2.55

Note: The best results are highlighted.

Table 8. Verification of hypothesis about exceedance of the smallest standard deviation received by different methods over the standard deviation received by non-force interaction method using Fisher criterion.

Base	L	$\min_{i\neq 9}\sigma_i$	σ_9	$\min_{i\neq 9}\sigma_i^2$	σ_9^2	$F_{n;n}=\frac{\min_{i\neq 9}\sigma_i^2}{\sigma_9^2}$	n	$F_{0,01;n;n}$	Confirmed hypothesis
"Russian"	1	**0.07842**	0.0809	0.00615	0.006545	1.064249*	32,758	1.02604	$\min_{i\neq 9}\sigma_i^2<\sigma_9^2$
	2	0.04028	**0.03951**	0.001622	0.001561	1.039357	65,238,532	1.00058	$\min_{i\neq 9}\sigma_i^2>\sigma_9^2$
"German"	1	0.08596	**0.08142**	0.007389	0.006629	1.11463	23,349	1.03092	$\min_{i\neq 9}\sigma_i^2>\sigma_9^2$
	2	0.05019	**0.04839**	0.002519	0.002342	1.075779	21,284,121	1.00101	$\min_{i\neq 9}\sigma_i^2>\sigma_9^2$

Continued

"Ukrainian"	1	0.06455	**0.06204**	0.004167	0.003849	1.082552	32,178	1.02628	$\min_{i \neq 9} \sigma_i^2 > \sigma_9^2$
	2	0.04561	**0.04491**	0.00208	0.002017	1.031416	42,253,549	1.00072	$\min_{i \neq 9} \sigma_i^2 > \sigma_9^2$
"English"	1	0.07768	**0.07466**	0.006034	0.005574	1.082536	16,783	1.03657	$\min_{i \neq 9} \sigma_i^2 > \sigma_9^2$
	2	0.04049	**0.03948**	0.001639	0.001559	1.05182	40,791,720	1.00073	$\min_{i \neq 9} \sigma_i^2 > \sigma_9^2$

* - there is a hypothesis considered about exceedance of standard deviation received by non-force interaction method over the smallest standard deviation received by other methods.

However, there is one exception, which is the Russian text. As it is shown in the results of additionally conducted experiments with other texts in Russian ("Anna Karenina" by Lev Tolstoy and "Master and Margarita" by Mikhail Bulgakov), this regularity is preserved. There was a separate research conducted, which showed that the main reason is four words that happen often and contain letter which almost do not appear in other combinations. Thus, in the word "всё" the probability of letter "с" being the predecessor of "ё" is 0.962389. The letter combination "сё" has significant synergetic effect as the probability of appearance of letter "с" equals 0.05327, whereas for letter "ё" it is 0.0004175. Therefore, for all letter combinations "асё", "бсё", …, "ясё" the combined conditional probability estimate p_9 ("с"/"аё"), p_9 ("с"/"бё"), …, p_9 ("с"/"яё") is calculated by deviation 0.962389 from 0.05327 (because letter "ё" provides the probability almost equal to 1 of the fact that there will be letter combination with letter "с" in it). However, in reality in the text, letter combinations "асё", "бсё", …, "ясё" (except "всё") did not appear (probability equals 0). The same case is for words "эт[о, а, у]". In these words, letter "э" appears with probability 0.90176.

Synergetic effect and restriction of choices in letter combinations for the stated words gives the difference in standard deviation which equals 0.00302. This exceeds common difference in deviations (0.00248, see Table 7, columns "Method 2" and "NFIM"). Without words "всё" and "это" the values of deviations are completely different (Table 9).

The verification showed that in other languages there are no such frequently used words that form total high probability of appearance of certain letters.

Experiment 3. Calculation of standard deviation of combined conditional probability estimate from statistical combined conditional probability of sequence of fragments of one part of texts using the approximation coefficients of the other texts.

Evaluation criterion: standard deviation (36).

As it was shown in experiment 1, there is a problem with using the methods which are based on approximation. Coefficients that give the biggest approximation of linear equation to the values of combined conditional probability in one text are not optimal for other texts. For example, coefficients of method 2 (see Table 7) for one-letter fragments of the Russian texts, which provide result even better than NFIM, were not the best for other texts. There were the experiments

Table 9. Standard deviation of combined conditional probability estimates from statistical combined conditional probability of text fragment sequence in "Russian" base.

Base	L	By unconditional probability	By 1st fragment	By 2nd fragment	By mean probability	Method 1	Method 2	Method 3	Method 4	**NFIM**	Advantage of NFIM (%) (37)
All words	1	0.09457	0.08879	0.09018	0.08228	0.08170	**0.07842**	0.08182	0.08117	0.08090	−3.05
Without words "всё" and "это"	1	0.095	0.08781	0.08957	0.08204	0.08112	0.07844	0.08079	0.08021	**0.0779**	0.7

Note: the best results are highlighted.

conducted which showed the increase of standard deviation if substituting coefficients of one part of texts with coefficients from the other texts (Table 10).

Taking into account the results provided in Table 10, it is possible to state once again that method which is based on the model of non-force interaction is universal (is suitable for different texts without changes in coefficients), while methods based on approximation can work effectively only with those texts for which the formula is developed (for example, only this piece of writing or, probably, works of only one writer).

Comment to experiments 2 and 3*. It has already been said that with set initial data (unconditional and certain conditional probabilities) it is impossible to calculate combined conditional probability. However, it can be evaluated. As it is seen from* Tables 7-10, *the biggest approximation to combined conditional probability is provided by non-force interaction method. Moreover, in methods that are based on approximation the calculation of coefficients was made from the position of minimum deviation from combined conditional probability (Formulas (28), (30), (32) and (34)). Nevertheless, non-force interaction method is still the best.*

Undoubtedly, any method, including the stated one, does not allow to calculate combined conditional probability precisely. The deviation of non-force interaction method is explained by the structure of natural language where a word is more than just the sum of letters, but also contents, because letters do not have contents, and a word has.

This is a synergetic effect of natural language. Earlier (in comments to Table 9*) it was explained how words "всё" and "это" influence the statistics. Indeed, if one letter from the text is taken, let it be "с", it speaks about nothing. There are a lot of possible words with this letter. For two letters "ст" the probability of appearance of any word containing letters "ст" is higher than probability of appearance of a word with letter "т" or "с". Let us add one more letter "ста". It is even higher. If we add letter "н", for this combination of letters (a word "стан" – "condition" in Ukrainian), the probability is almost 1. Therefore, for more "informative" letter combinations the probability tends to 1, and for non-informative it tends to 0. This creates a deviation when using any other method. However,*

Table 10. Standard deviation of estimates from probability of text fragment sequence by non-force interaction method and approximation methods with different coefficients.

Base	Base from which coefficients are taken	L	Approximation methods				**Non-Force Interaction Method**
			Method 1	Method 2	Method 3	Method 4	
"Russian"	"Russian"	1	0.08170	**0.07842**	0.08182	0.08117	0.08090
		2	0.04107	0.04028	0.04106	0.04073	**0.03951**
	"German"	1	0.08226	**0.07937**	0.08243	0.08181	0.08090
		2	0.04109	0.04039	0.04109	0.04078	**0.03951**
"German"	"German"	1	0.08714	0.08690	0.08559	0.08596	**0.08142**
		2	0.05110	0.05019	0.05102	0.05058	**0.04839**
	"English"	1	0.08727	0.08698	0.08561	0.08597	**0.08142**
		2	0.05112	0.05024	0.05104	0.05059	**0.04839**
"Ukrainian"	"Ukrainian"	1	0.06694	0.06486	0.06544	0.06455	**0.06204**
		2	0.04637	0.04561	0.04634	0.04589	**0.04491**
	"Russian"	1	0.06723	0.06500	0.06595	0.06489	**0.06204**
		2	0.04642	0.04562	0.04640	0.04596	**0.04491**
"English"	"English"	1	0.07845	0.07769	0.07768	0.07787	**0.07466**
		2	0.04127	0.04049	0.04124	0.04092	**0.03948**
	"Ukrainian"	1	0.07854	0.07831	0.07787	0.07825	**0.07466**
		2	0.04134	0.04060	0.04131	0.04120	**0.03948**

Note: the best results are highlighted.

the fact that the non-force interaction method gives the smallest deviation from statistical combined conditional probability confirms that in the mechanisms of speech production (human intellectual apparatus) the processes of interaction can be based on the algorithms which result from the information-probabilistic interpretation of mechanical movement.

It is no wonder, probably, that in the basis of different processes of interaction (on micro- and macro-levels of matter existence) there are same laws. It would be strange if this did not happen. Thus, it can be used in many situations, including the development of artificial intelligence systems.

One of the tasks connected to such systems is the task of predicting. To create a reliable forecast in stochastic subject fields, it is not really crucial which is the probability of occurrence of all events, the most important is which event has the highest probability. There were conducted experimental researches that allow to determine the most probable text fragment by the highest estimate of combined conditional probability using different methods. Let us consider the results.

Experiment 4. Forecasting of text fragment sequence

<u>Evaluation criterion: the percentage of correctly predicted text fragments (38)</u>

The forecast is based on the choice of the biggest combined conditional probability estimate (38). As a result of processing of the texts results stated in Table 11 were obtained.

As it can be seen in Table 11, the advantage of the non-force interaction method is rather substantial. Among the methods which are based on linear approximation the best is the one that uses the difference between the smallest conditional probability and unconditional probability (33). Moreover, it is more effective than the approximation methods that are oriented at conditional probabilities only. However, it is the deviation of conditional probability from unconditional one that interprets relative velocity of objects and is in the basis of the Formula (19). This, once again, confirms that in a human brain the value of non-force (information) action is represented by the deviation of conditional probability of certain reaction (in experiments it was language) from unconditional one. Returning to NFIM, it gives the best result even without aiming at the selection of the biggest conditional probability (which is dictated with the formulas 29, 33).

Experiment 5. Ranking of estimates of combined conditional probability of text fragment sequence.

Criterion of evaluation: deviation in ranks (40)

Within experiments, there was made ranking of probability estimates with comparison with the ranks of the probabilities themselves. The deviation of ranks of combined conditional probability estimates received by different methods from the rank of statistical combined conditional probability was evaluated. The deviation in ranks by Formula (40) for different methods is provided in Table 12.

The received distribution of ranks states even bigger advantage of non-force interaction method in comparison with others provided in this paper. With the

Table 11. Forecasting of text fragment sequence by different methods.

Base	L	By unconditional probability (μ_1)	By 1st fragment (μ_2)	By 2nd fragment (μ_3)	By mean probability (μ_4)	Method 1 (μ_5)	Method 2 (μ_6)	Method 3 (μ_7)	Method 4 (μ_8)	NFIM (μ_9)	Advantage of NFIM (%) (39)
"Russian"	1	11.54	19.37	19.17	22.92	22.88	25.61	25.22	26.19	**27.98**	6.40
	2	1.77	12.58	12.88	20.06	20.04	26.45	20.15	25.08	**28.02**	5.60
"German"	1	16.05	26.97	26.64	34.27	33.25	35.80	35.22	36.76	**38.44**	4.37
	2	3.63	15.83	13.89	22.90	22.89	26.28	23.43	26.62	**30.25**	12.00
"Ukrainian"	1	9.21	17.30	17.72	21.77	21.42	24.28	23.36	25.21	**25.83**	2.40
	2	1.34	9.12	9.63	15.38	15.38	19.93	15.44	19.94	**22.48**	11.30
"English"	1	11.79	22.35	21.93	28.11	27.86	29.21	28.66	29.25	**30.39**	3.75
	2	3.19	12.61	12.36	19.44	19.33	23.35	19.89	23.06	**25.61**	8.82

Note: the best results are highlighted.

help of this method, it is possible to determined more exactly which of the variations of forecast can be counted upon and which cannot.

Experiment 6. The graph of deviation of combined conditional probability estimate received by the non-force interaction method from statistical combined conditional probability of text fragment sequence.

The deviations of values of combined conditional probability received by the non-force interaction method from statistical combined conditional probability of text fragment sequence in "English" base which were received in the process of experiments are provided in Table 13. According to these data, the graph was created (Figure 3)

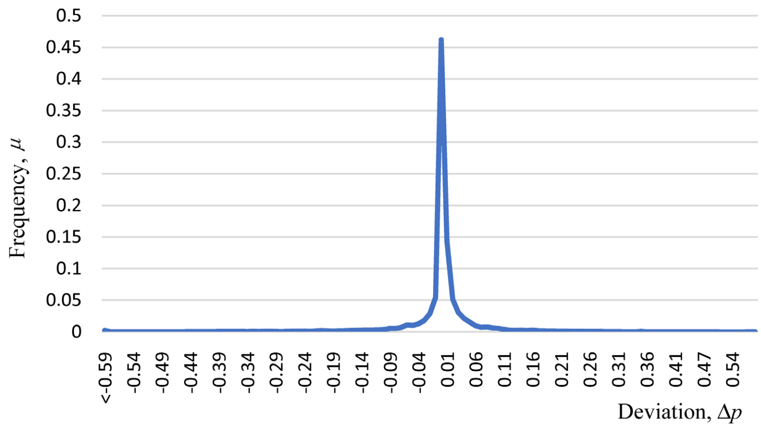


Figure 3. Distribution of deviation of combined conditional probability estimate received by non-force interaction method from its statistical value in "English" base (one-letter fragments).

Table 12. Standard deviation of ranks of combined conditional probability estimates and the rank of conditional probability of text fragment sequence.

Base	L	% of correct prediction of text fragment sequence									Advantage of NFIM (%) (41)
		By unconditional probability	By 1st fragment	By 2nd fragment	By mean probability	Method 1	Method 2	Method 3	Method 4	**Non-force interaction method**	
"Russian"	1	37.74	25.71	24.19	19.62	19.65	16.38	17.28	19.18	**11.48**	42.62
	2	21.88	14.63	14.59	11.80	11.81	11.27	10.89	11.17	**8.98**	21.30
"German"	1	24.10	18.11	13.11	12.47	12.99	11.61	10.85	10.70	**7.60**	40.85
	2	20.02	14.17	12.11	11.18	11.20	10.15	10.11	9.78	**7.52**	30.03
"Ukrainian"	1	41.62	27.53	25.18	23.81	23.91	18.28	19.76	17.09	**10.07**	69.78
	2	3.27	2.07	2.15	1.84	1.84	1.74	1.73	1.62	**1.50**	8.03
"English"	1	30.99	19.32	18.52	14.78	14.87	13.40	12.43	13.02	**8.74**	42.21
	2	63.06	42.61	41.05	32.79	32.79	31.63	29.96	31.07	**24.62**	21.69

Note: the best results are highlighted.

Table 13. The deviation of combined conditional probability estimate received by non-force interaction method ("English" base) from statistical combined conditional probabilities.

Deviation	Quantity
≤−0.60	32
−0.59	1
−0.57	2
−0.56	3
−0.55	4
−0.54	1
−0.53	1
−0.52	2
−0.51	1
−0.5	5
−0.49	5
−0.48	3
−0.47	3
−0.46	6
−0.45	1
−0.44	2
−0.43	5
−0.42	6
−0.41	8
−0.4	6
−0.39	6
−0.38	12
−0.37	9
−0.36	6
−0.35	10
−0.34	6
−0.33	14
−0.32	8
−0.31	13
−0.3	12
−0.29	10
−0.28	5

Continued

−0.27	13
−0.26	15
−0.25	16
−0.24	19
−0.23	12
−0.22	21
−0.21	29
−0.2	20
−0.19	18
−0.18	24
−0.17	30
−0.16	29
−0.15	35
−0.14	38
−0.13	43
−0.12	43
−0.11	46
−0.1	52
−0.09	75
−0.08	77
−0.07	98
−0.06	151
−0.05	141
−0.04	177
−0.03	250
−0.02	403
−0.01	762
0	6471
0.01	2015
0.02	724
0.03	427
0.04	298
0.05	212
0.06	135
0.07	99

Continued

0.08	105
0.09	89
0.1	78
0.11	52
0.12	36
0.13	38
0.14	39
0.15	27
0.16	39
0.17	25
0.18	26
0.19	26
0.2	19
0.21	15
0.22	13
0.23	12
0.24	11
0.25	17
0.26	14
0.27	7
0.28	8
0.29	5
0.3	9
0.31	5
0.32	4
0.33	3
0.34	2
0.35	9
0.36	2
0.37	4
0.38	3
0.39	4
0.4	5
0.41	2
0.42	5

Continued

0.43	3
0.45	1
0.46	2
0.47	1
0.48	2
0.49	1
0.5	1
0.51	1
0.54	1
0.55	1
0.56	1
0.59	1
≥0.60	5

As it can be seen from the graph, the received combined conditional probability estimates differ slightly from combined conditional probabilities themselves and form the peak of distribution in point "0" (deviation is absent).

To confirm the received results, there were conducted additional experiments which did not characterise the accuracy of determination of text structure, but rather show the versatility of methods developed in the non-force interaction theory.

11. Additional Experimental Researches

As it can be seen from the tables stated in Section 10, the best result is provided by the method based on the non-force interaction theory, even though, from the point of view of probabilistic approach, the approximation-based methods should be better, as coefficients for equations are chosen in such a way that they should give the smallest deviation square, thus the biggest approximation to the probabilities themselves.

Thus, a question arises. What if non-force interaction method does not operate the information part of the text production, but rather uses only the deviations of probabilities as a characteristics of fragment sequence appearance in a text? In this way, the information-probabilistic interpretation of mechanical movement is not reflected in a human brain during text production? In order to verify or deny this, the following experiment was conducted.

Experiment 7. Research of random texts with even distribution of the letters of alphabet.

<u>Evaluation criterion: all stated in Section 7.</u>

There were texts generated, the sizes of which were equal to those used in experiments, but they had equal distribution of letter sequence. Of course, when increasing the size of text indefinitely there would be received the following value of probabilities:

$$p\left(a_i/a_{i-1}a_{i+1}\right) \approx p\left(a_i/a_{i-1}\right) \approx p\left(a_i/a_{i+1}\right) \approx p\left(a_i\right).$$

Therefore, all methods used in this paper would give the same result!

When the size of the text is limited, it is highly likely that there will be deviations of values of conditional probabilities from unconditional ones. In this case, the results of predicting of text fragment sequence and standard deviation of probability estimates made by different methods will be different.

In total, for each language, there were generated 40 random texts equal by the size to the texts of bases used. Standard deviations of combined conditional probability estimates from combined conditional probabilities of text fragment sequence of a random text are shown in Table 14. Mean values of the forecast of text fragments made by different methods are shown in Table 15. The deviations in ranks are in Table 16. In contrast to the experiments with real texts, here only one-letter fragments were used, as even distribution is the same for both one- and two-letter fragments. Moreover, for one-letter pieces, each fragment appears more often. Therefore, the statistics is better.

Table 14. Standard deviation of estimates from fragment sequence probabilities for the texts with even distribution of the letters of alphabet ($\sigma \cdot 10^2$).

Text by base size	By unconditional probability	By 1st fragment	By 2nd fragment	By mean probability	Method 1	Method 2	Method 3	Method 4	**NFIM**	Advantage of NFIM (%) (37)
"Russian"	0.323559	0.318828	0.318831	0.316438	0.314176	0.314174	**0.314028**	**0.314026**	0.314028	−0.000695
"German"	0.461893	0.454350	0.454352	0.450529	0.446929	0.446920	0.446682	**0.446675**	0.446677	−0.000373
"Ukrainian"	0.686833	0.676246	0.676257	0.670897	0.665845	0.665828	0.665501	0.665487	0.665485	0.000275
"English"	0.195578	0.192050	0.192052	0.190263	0.188596	0.188591	**0.188458**	**0.188453**	0.188459	−0.003413

Note: highlighted are the results which are better than those received by the non-force interaction method.

Table 15. Average number of correctly determined text fragments by 40 random generation of text with even distribution of the letters of alphabet.

Text by base size	By unconditional probability	By 1st fragment	By 2nd fragment	By mean probability	Method 1	Method 2	Method 3	Method 4	**NFIM**	Advantage of NFIM (%) (39)
"Russian"	78999.1	81436.3	81426.3	82665.6	82664.8	82659.4	**82691.9**	**82691.1**	82688.9	−0.003659
"German"	42545.5	44295.3	44271.9	45212.1	45213.0	45213.4	45228.9	**45236.5**	45235.5	−0.002155
"Ukrainian"	20153.7	21463.4	21477.5	22175.2	22176.6	**22184.0**	22170.3	22172.4	22177.1	−0.030888
"English"	183095.9	185953.9	185933.2	187219.2	187214.9	187241.0	187277.4	187267.9	187,278.7	0.000674

Note: highlighted are the results which are better than those received by the non-force interaction method.

Table 16. Deviation in ranks of estimates and probabilities of fragment sequence for the texts with even distribution of the letters of alphabet.

Text by example of base	% correct prediction of text fragment sequence									Advantage of NFIM (%)
	By unconditional probability	By 1^{st} fragment	By 2^{nd} fragment	By mean probability	Method 1	Method 2	Method 3	Method 4	**NFIM**	
"Russian"	164.760	139.896	139.819	130.470	130.486	130.485	130.215	**130.206**	130.210	−0.00769
"German"	134.129	112.559	112.505	104.600	104.623	104.611	104.378	**104.364**	104.373	−0.01375
"Ukrainian"	146.245	121.950	121.923	114.341	114.372	114.365	**114.105**	**114.098**	114.106	−0.01675
"English"	104.389	88.326	88.238	81.159	81.169	81.158	**80.918**	**80.913**	80.923	−0.03079

Note: highlighted are the results which are better than those received by the non-force interaction method.

As it can be seen from Tables 14-16, method based on the non-force interaction theory is inferior by almost all points comparing to the methods which use the approximation of probabilities. It means that it is the content part of the text, the processes of interaction that form what the method "processes", and not just probabilities. However, for "random" text, it is not better than the methods of approximation, as it should be according to classical mathematical principles.

In Table 14, it can be seen that the more the size of the text is, the smaller is standard deviation. This complies with the idea that for "indefinite" sizes of random texts all probability estimates will be equal to probabilities themselves.

The non-force interaction method is the best only for small sizes of texts ("Ukrainian" base) (see Table 14). However, even in this case, the advantage is minimum (0.000275%). Such exception only confirms the rule that the non-force interaction method works best with the objects that include the idea (meaning). This, in its turn, once more proves the important role of the non-force (informational) interactions when producing a text. Moreover, it also proves that processes of text production in a human brain correspond to the non-force interaction model which was received from information-probabilistic interpretation of mechanical movement and is the basis of the non-force interaction theory.

The NFIM was worse than other methods at ranking probability estimates (see Table 16). Comparing with Table 12, it is possible to reiterate that the non-force interaction method is effective only for "sensible" (intelligent) rather than random texts. This characterizes the level of influence of mechanics of natural text creating in a human brain (including forming of words) which is recognized by the non-force interaction method. Therefore, this means it is the contextual part of language that it operates with. Thus, this part of language functions according to the laws which are depicted in the non-force interaction method, that is movement and direct (contact) interaction in the information-probabilistic interpretation. Hence, what if it is not an interpretation but rather a reality?

Furthermore, what can happen if all texts are combined into one? There was an experiment with the text conducted which includes all four bases: Russian, German, Ukrainian and English.

Experiment 8. The research of a combined text

Criterion of evaluation: all stated in Section 7.

There were the rates of effectiveness developed for the combined text: standard deviation from combined conditional probability (Table 17) and quantity of correctly predicted text fragments (Table 18). Apart from that, the deviation of probability estimate rank from combined conditional probability rank was evaluated for the combined text (Table 19).

What can be seen from Tables 17-19? All rates of the NFIM are much higher than for other methods! Even if compared with linear approximation. By the way, the author tried using linear approximation, that is deviation square of conditional probability from an unconditional one. Of course, it does not eliminate the possibility of that someone will discover such an equation which will

Table 17. Standard deviation of estimates from probabilities of text fragment sequence of combined text.

L	By unconditional probability	By 1st fragment	By 2nd fragment	By mean probability	Method 1	Method 2	Method 3	Method 4	**NFIM**	Advantage of NFIM (%) (37)
1	0.09561	0.08543	0.08991	0.08024	0.07874	0.07693	0.07800	0.07765	**0.07508**	2.46
2	0.04628	0.04535	0.04527	0.04423	0.04404	0.04324	0.04401	0.04365	**0.04230**	2.22

Note: the best results are highlighted.

Table 18. Quantity of correctly predicted fragments of combined text.

L	By unconditional probability	By 1st fragment	By 2nd fragment	By mean probability	Method 1	Method 2	Method 3	Method 4	**NFIM**	Fragment total	Advantage of NFIM (%) (39)
1	894,574	1,617,312	1,595,614	2,001,922	1,992,145	2,136,515	2,083,939	2,165,393	**2,260,531**	7,456,824	4.21
2	201,116	957,000	946,025	1,479,064	1,476,830	1,826,359	1,498,931	1,794,563	**1,991,002**	7,456,816	8.27

Note: the best results are highlighted.

Table 19. Deviations in estimate ranks from ranks of fragment sequence probability of combined text.

L	By unconditional probability	By 1st fragment	By 2nd fragment	By mean probability	Method 1	Method 2	Method 3	Method 4	**NFIM**	Advantage of NFIM (%) (41)
1	35.10	23.62	21.33	18.65	18.79	15.80	15.93	15.79	**9.79**	61.27
2	34.80	23.54	22.64	18.36	18.36	17.60	16.80	17.53	**13.72**	22.47

Note: the best results are highlighted.

give bigger approximation to combined conditional probability than the NFIM for some text. As in "Russian" base, where there are one-letter fragments (see **Table 7**). However, whether this equation will fit other texts it unknown. According to the results stated in **Table 10**, it is highly unlikely.

As it can be seen from the provided tables (see **Table 11** and **Table 18**), the approximation method which operates with deviations of conditional probability from an unconditional one (33) is not bad for forecasting, which Method 4. Therefore, the question arises. What if this difference is replaced with the non-force action value received in NFIT (which is also based on the difference between unconditional and conditional probability), how will the forecast change?

Experiment 9. Comparison of the effectiveness of the methods which are based on the deviation of conditional probability from an unconditional one and the value of non-force influence.

Criterion of evaluation: the percentage of correctly predicted text fragments (38).

Since method 4 is quite effective for predicting text fragment sequence, it is proposed to replace the difference between conditional and unconditional probability with the value of non-force influence (in the basis of which there is also a deviation of conditional probability from an unconditional one) (19), and the deviation of estimate from probability is replaced by achievement of the maximum results in predicting of the texts:

$$p_8\left(a_i/a_{i-1}a_{i+1}\right)=\delta_1\cdot p_i^{\max}+\delta_2\cdot\left(p_i^{\min}-p\left(a_i\right)\right)+\delta_3.$$

Let us apply Formula (9) in Formula (19) and "improve" Formula (33), replacing the difference in probabilities with non-force influence value

$$p_{10}\left(a_i/a_{i-1}a_{i+1}\right)=\delta_1\cdot p_i^{\max}+\delta_2\cdot\left(d_i^{\min}\cdot\sqrt{d\left(a_i\right)^2+1}-d\left(a_i\right)\cdot\sqrt{\left(d_i^{\min}\right)^2+1}\right)+\delta_3, \tag{42}$$

under the condition that

$$\mu_8\left(\delta_1,\delta_2\right)\cdot\sum_{a_{i-1}a_{i+1}}n\left(a_{i-1}a_{i+1}\right)\to\max; \tag{43}$$

$$\mu_{10}\left(\delta_1,\delta_2\right)\cdot\sum_{a_{i-1}a_{i+1}}n\left(a_{i-1}a_{i+1}\right)\to\max, \tag{44}$$

where $\mu_8\left(\delta_1,\delta_2\right)$ is the percentage of correct predictions of text fragment sequence by method 4; $\mu_{10}\left(\delta_1,\delta_2\right)$ is the percentage of correct predictions of text fragment sequence by method 5; $p_{10}\left(a_i/a_{i-1}a_{i+1}\right)$ is the estimate of conditional probability of sequence of text fragment a_i by linear approximation of non-force influence of the fragment with the smallest conditional probability: if the previous text fragment is a_{i-1}; if the following text fragment is a_{i+1} (Method 5); δ_1,δ_2 are approximation coefficients; $d_i^{\min}$ is the amount of information that triggers the reaction, which is calculated by Formula (11) with argument $p_i^{\min}$; $d\left(a_i\right)$ is the amount of information that triggers the reaction, which is calculated by Formula (11) with argument $p\left(a_i\right)$.

The results of predicting made by such combined method (method 5) are provided in Table 20. The result once again confirms higher descriptiveness of non-force interaction method regarding calculation of combined conditional probability, for example, the actions of artificial intelligence systems, and its higher "usefulness" in solving problems of predicting.

Experiment 10. Using instead of unconditional probability the conditional one, which excludes the cases when previous and subsequent fragments are the current ones.

Criterion of evaluation: all stated in Section 7.

To calculate the values of influence, it would be necessary to use conditional probability which would not include those cases when previous fragment was a_{i-1} and the following was a_{i+1}. Then the non-force value itself would exactly reflect the appearance of these fragments. However, the research has shown

$$p(a_i) \approx p\left(a_i / \overline{a_{i-1}}\right);$$

$$p(a_i) \approx p\left(a_i / \overline{a_{i+1}}\right),$$

where $p\left(a_i / \overline{a_{i-1}}\right)$ is statistical conditional probability of the sequence of fragment a_i when the previous fragment was not a_{i-1}; $p\left(a_i / \overline{a_{i+1}}\right)$ is statistical conditional probability of the sequence of fragment a_i when the following fragment is not a_{i+1}.

This was verified in the selected texts. The results are provided in Table 21.

Table 20. Comparison of approximation methods oriented at predicting of combined text fragments.

L	Quantity of correctly determined text fragments	
	Method 4	Method 5
1	2,242,440	**2,259,673**
2	1,985,547	**2,000,457**

Note: the best results are highlighted.

Table 21. Deviation of unconditional probabilities from conditional probabilities with exclusion of reviewed fragments.

Base	L	Deviation of probability		% deviation	
		Mean	Maximum	Mean	Maximum
"Russian"	1	0.000746	0.003368	2.460	11.115
	2	0.000002	0.000022	0.147	2.083
"German"	1	0.000887	0.004520	2.662	13.560
	2	0.000003	0.000073	0.195	5.257
"Ukrainian"	1	0.000830	0.002823	2.655	9.034
	2	0.000002	0.000016	0.145	1.500
"English"	1	0.001045	0.003581	2.717	9.310
	2	0.000003	0.000064	0.199	3.923

Nevertheless, in order to avoid doubts regarding the objectivity of the received results, there were conducted experiments using provided conditional probabilities $p\left(a_i/\overline{a_{i-1}}\right)$, $p\left(a_i/\overline{a_{i+1}}\right)$ instead of unconditional $p(a_i)$. The results are stated in Tables 22-24.

As it can be seen in Tables 22-24, the non-force interaction method remains the best of all others.

Experiment 11. Consideration of the combinations of fragments in which both conditional probabilities of appearance of a text fragment are not equal to zero ($p(a_i/a_{i-1})>0$, $p(a_i/a_{i+1})>0$).

Table 22. Standard deviation of combined conditional probability estimates from statistical combined conditional probability of text fragment sequence using conditional probabilities $p\left(a_i/\overline{a_{i-1}}\right), p\left(a_i/\overline{a_{i+1}}\right)$ instead of unconditional probabilities.

Base	L	By unconditional probability	By 1st fragment	By 2nd fragment	By mean probability	Method 1	Method 2	Method 3	Method 4	**NFIM**	Advantage of NFIM (%)
"Russian"	1	0.09545	0.08880	0.09019	0.08228	0.08170	**0.07843**	0.08176	0.08120	0.08107	−3.26
	2	0.04314	0.04236	0.04227	0.04121	0.04107	0.04028	0.04106	0.04074	**0.03952**	1.94
"German"	1	0.11050	0.09320	0.10388	0.08973	0.08715	0.08690	0.08565	0.08617	**0.08233**	4.03
	2	0.05481	0.05296	0.05323	0.05148	0.05110	0.05019	0.05102	0.05058	**0.04838**	3.73
"Ukrainian"	1	0.08394	0.07339	0.07588	0.06849	0.06694	0.06486	0.06543	0.06469	**0.06223**	3.95
	2	0.04804	0.04731	0.04715	0.04662	0.04637	0.04561	0.04634	0.04589	**0.04490**	1.58
"English"	1	0.10177	0.08646	0.09298	0.08130	0.07845	0.07769	0.07775	0.07808	**0.07504**	3.53
	2	0.04394	0.04292	0.04265	0.04149	0.04127	0.04049	0.04124	0.04093	**0.03948**	2.55

Note: the best results are highlighted.

Table 23. Predicting of text fragment sequence by different methods using conditional probabilities $p\left(a_i/\overline{a_{i-1}}\right), p\left(a_i/\overline{a_{i+1}}\right)$ instead of unconditional probabilities.

Base	L	By unconditional probability (μ_1)	By 1st fragment (μ_2)	By 2nd fragment (μ_3)	By mean probability (μ_4)	Method 1 (μ_5)	Method 2 (μ_6)	Method 3 (μ_7)	Method 4 (μ_8)	**NFIM (μ_9)**	Advantage of NFIM (%) (39)
"Russian"	1	11.54	19.37	19.17	22.92	22.88	25.61	25.36	26.17	**27.66**	5.39
	2	1.77	12.58	12.88	20.06	20.04	26.45	20.16	25.04	**27.84**	4.99
"German"	1	16.05	26.97	26.64	34.27	33.25	35.80	35.28	36.65	**37.39**	1.98
	2	3.31	15.83	13.89	22.90	22.89	26.28	23.45	26.59	**30.00**	11.37
"Ukrainian"	1	6.62	17.30	17.72	21.77	21.42	24.28	23.79	25.15	**25.60**	1.76
	2	0.74	9.12	9.63	15.38	15.38	19.93	15.45	19.90	**22.40**	11.03
"English"	1	11.79	22.35	21.93	28.11	27.86	29.21	28.64	29.26	**29.86**	2.01
	2	3.19	12.61	12.36	19.44	19.33	23.35	19.89	23.01	**25.43**	8.18

Note: the best results are highlighted.

Table 24. Standard deviation of ranks of combined conditional probability estimates from ranks of statistical combined conditional probabilities of text fragment sequence using conditional probabilities $p\left(a_i/\overline{a_{i-1}}\right), p\left(a_i/\overline{a_{i+1}}\right)$.

Base	L	% of correct prediction of text fragment sequence									Advantage of NFIM (%) (41)
		By unconditional probability	By 1st fragment	By 2nd fragment	By mean probability	Method 1	Method 2	Method 3	Method 4	**Non-force interaction method**	
"Russian"	1	40.32	25.71	24.19	19.62	19.65	16.38	17.44	19.52	**11.43**	43.33
	2	22.72	14.63	14.59	11.80	11.81	11.27	10.90	11.17	**9.05**	20.38
"German"	1	26.12	18.11	13.11	12.47	12.99	11.61	10.90	10.94	**7.64**	42.61
	2	21.07	14.17	12.11	11.18	11.20	10.15	10.12	9.84	**7.61**	29.22
"Ukrainian"	1	44.41	27.53	25.18	23.81	23.91	18.28	19.63	17.30	**10.14**	70.61
	2	3.37	2.07	2.15	1.84	1.84	1.74	1.73	1.62	**1.50**	7.78
"English"	1	33.74	19.32	18.52	14.78	14.87	13.40	12.61	13.28	**8.91**	41.42
	2	65.33	42.61	41.05	32.79	32.79	31.63	29.99	31.10	**24.75**	21.15

Note: the best results are highlighted.

Criterion of evaluation: all stated in Section 7.

One more experiment was connected to the decision accepted in the methodology of experimental research. It is to consider combinations of fragments for which at least one probability is not equal to zero (pp.6 of Section 5): $n(a_{i-1}, a_i) > 0$, or $n(a_i, a_{i+1}) > 0$. Since, under the condition that $n(a_{i-1}, a_i) = 0$ or $n(a_i, a_{i+1}) = 0$, combined conditional probability estimate calculated by the non-force interaction method will also be equal to zero, this does not create additional advantage to it comparing with others.

However, from the point of view of the development of artificial intelligence systems this approach is correct. As it is not improbable that when increasing the statistics, zero probability will become not equal to zero. Hence, these cases should be considered, too.

Results are provided in Tables 25-27.

As it can be seen from Tables 25-27, the change of methodology does not violate previous result, when the non-force interaction method is the most effective (according to the criteria stated in Section 7) of all others.

For artificial intelligence systems, it is highly important to have consistency of received results under different conditions. Usually, to verify any methods, samplings are divided into training and control ones. Probabilities received in training samplings and coefficients of approximation equations are applied to the control sampling. Within experimental research, the results of which are provided in this article, there also was such an experiment.

Experiment 12. Research of the text divided into training and control samplings.

Criterion of evaluation: all stated in Section 7.

To have objective results, especially those concerning approximation methods, all the texts were divided randomly into two samplings, each having 50% the size of the text: training and control. By the training sampling, approximation coefficients and unconditional probabilities of text fragment appearance were calculated. In the control sampling, according to the criteria described in Section 7, the effectiveness of provided methods was verified. The results are stated in Tables 28-30.

As it is seen from Tables 28-30, there has nothing changed. The NFIM is the best and its advantage over the other methods in some cases even increased (see Table 7, Table 11, Table 12).

Table 25. Standard deviation of combined conditional probability estimates from statistical combined conditional probability of text fragment sequence under the condition: $p(a_i/a_{i-1})>0$ and $p(a_i/a_{i+1})>0$.

Base	L	By unconditional probability	By 1st fragment	By 2nd fragment	By mean probability	Method 1	Method 2	Method 3	Method 4	**NFIM**	Advantage of NFIM (%) (37)
"Russian"	1	0.10384	0.09712	0.09882	0.09044	0.08966	**0.08653**	0.08974	0.08894	0.08943	−3.24
	2	0.08976	0.08699	0.08672	0.08522	0.08404	0.08312	0.08395	0.08301	**0.08237**	0.78
"German"	1	0.12585	0.10803	0.11927	0.10399	0.10074	0.10063	0.09885	0.09900	**0.09507**	3.98
	2	0.12943	0.12273	0.12361	0.12064	0.11757	0.11694	0.11714	0.11610	**0.11469**	1.23
"Ukrainian"	1	0.08782	0.07757	0.08030	0.07262	0.07083	0.06888	0.06924	0.06826	**0.06601**	3.40
	2	0.10761	0.10501	0.10463	0.10401	0.10212	0.10141	0.10194	0.10088	**0.10076**	0.12
"English"	1	0.10856	0.09373	0.10035	0.08808	0.08480	0.08405	0.08407	0.08413	**0.08111**	3.61
	2	0.08147	0.07850	0.07817	0.07652	0.07534	0.07451	0.07521	0.07446	**0.07341**	1.43

Note: the best results are highlighted.

Table 26. Predicting of text fragment sequence by different methods under the condition: $p(a_i/a_{i-1})>0$ and $p(a_i/a_{i+1})>0$.

Base	L	By unconditional probability (μ_1)	By 1st fragment (μ_2)	By 2nd fragment (μ_3)	By mean probability (μ_4)	Method 1 (μ_5)	Method 2 (μ_6)	Method 3 (μ_7)	Method 4 (μ_8)	**NFIM (μ_9)**	Advantage of NFIM (%) (39)
"Russian"	1	11.56	19.42	19.17	22.95	22.98	25.50	25.27	26.39	**27.98**	5.68
	2	2.66	15.51	15.49	21.72	21.69	26.46	21.85	27.11	**28.02**	3.25
"German"	1	16.19	27.02	26.85	34.32	33.32	35.70	35.98	36.79	**38.44**	4.29
	2	5.42	19.08	17.73	24.86	24.86	26.49	25.52	28.40	**30.25**	6.12
"Ukrainian"	1	9.42	17.41	17.73	21.78	21.50	24.15	23.40	25.21	**25.83**	2.40
	2	2.47	12.56	13.04	17.95	17.94	20.62	18.18	21.86	**22.48**	2.76
"English"	1	11.89	22.36	21.95	28.11	27.75	29.07	28.63	29.31	**30.39**	3.55
	2	4.18	14.23	13.82	20.26	20.20	23.15	20.75	24.22	**25.61**	5.43

Note: the best results are highlighted.

Table 27. Standard deviation of ranks of combined conditional probability estimates from the ranks of statistical combined conditional probabilities of text fragment sequence under the condition: $p(a_i/a_{i-1}) > 0$ and $p(a_i/a_{i+1}) > 0$.

Base	L	% of correct prediction of text fragment sequence									Advantage of NFIM (%)
		By unconditional probability	By 1st fragment	By 2nd fragment	By mean probability	Method 1	Method 2	Method 3	Method 4	**NFIM**	
"Russian"	1	37.74	25.71	24.19	19.62	19.66	16.51	17.26	19.75	**11.48**	43.77
	2	21.88	14.63	14.59	11.80	11.81	11.22	10.90	11.48	**8.98**	21.34
"German"	1	24.10	18.11	13.11	12.47	12.89	11.84	10.72	10.86	**7.60**	41.09
	2	20.02	14.17	12.11	11.18	11.20	10.48	10.10	9.84	**7.52**	30.90
"Ukrainian"	1	41.62	27.53	25.18	23.81	23.91	18.62	19.76	17.05	**10.07**	69.32
	2	3.27	2.07	2.15	1.84	1.84	1.75	1.73	1.63	**1.50**	8.71
"English"	1	30.99	19.32	18.52	14.78	14.88	13.48	12.42	13.27	**8.74**	42.06
	2	63.06	42.61	41.05	32.79	32.79	31.43	29.96	31.91	**24.62**	21.66

Note: the best results are highlighted.

Table 28. Standard deviation of combined conditional probability estimates from statistical combined conditional probability of text fragment sequence in control text sampling.

Base	L	By unconditional probability	By 1st fragment	By 2nd fragment	By mean probability	Method 1	Method 2	Method 3	Method 4	**NFIM**	Advantage of NFIM (%) (37)
"Russian"	1	0.09627	0.09058	0.09147	0.08388	0.08189	**0.07887**	0.08181	0.08116	0.08217	−4.01
	2	0.04718	0.04629	0.04623	0.04518	0.04478	0.04387	0.04477	0.04435	**0.04324**	1.45
"German"	1	0.11047	0.09504	0.10505	0.09139	0.09011	0.08998	0.08863	0.08908	**0.08278**	7.06
	2	0.05956	0.05748	0.05777	0.05601	0.05537	0.05436	0.05526	0.05473	**0.05256**	3.42
"Ukrainian"	1	0.08554	0.07608	0.07845	0.07129	0.06995	0.06790	0.06857	0.06772	**0.06470**	4.66
	2	0.05486	0.05398	0.05385	0.05325	0.05256	0.05155	0.05252	0.05187	**0.05116**	0.78
"English"	1	0.10079	0.08688	0.09318	0.08161	0.07838	0.07742	0.07758	0.07769	**0.07487**	3.41
	2	0.04686	0.04571	0.04552	0.04437	0.04407	0.04327	0.04403	0.04368	**0.04222**	2.47

Note: the best results are highlighted.

Table 29. Predicting of fragment sequence of control text sampling made by different methods.

Base	L	By unconditional probability (μ_1)	By 1st fragment (μ_2)	By 2nd fragment (μ_3)	By mean probability (μ_4)	Method 1 (μ_5)	Method 2 (μ_6)	Method 3 (μ_7)	Method 4 (μ_8)	**NFIM (μ_9)**	Advantage of NFIM (%) (39)
"Russian"	1	11.57	19.37	19.19	23.11	23.20	25.54	25.37	26.24	**28.05**	−4.01
	2	1.79	12.61	12.94	20.16	20.16	26.59	20.24	25.55	**28.44**	1.45

Continued

"German"	1	16.00	26.92	26.64	34.28	33.56	35.73	35.24	36.72	**38.44**	7.06
	2	3.64	15.87	13.98	22.87	22.85	26.30	23.40	26.83	**30.53**	3.42
"Ukrainian"	1	9.24	17.39	17.72	21.66	21.65	24.22	23.75	25.47	**25.98**	4.66
	2	1.38	9.22	9.82	15.82	15.81	20.91	15.91	21.25	**23.67**	0.78
"English"	1	11.79	22.34	21.90	28.13	27.66	29.22	28.64	29.25	**30.41**	3.41
	2	3.20	12.62	12.36	19.40	19.38	23.39	19.91	23.10	**25.70**	2.47

Note: the best results are highlighted.

Table 30. Standard deviation of ranks of combined conditional probabilities estimates from ranks of statistical combined conditional probabilities of fragment sequence from control text sampling.

Base	L	% of correct prediction of text fragment sequence									Advantage of NFIM (%)
		By unconditional probability	By 1st fragment	By 2nd fragment	By mean probability	Method 1	Method 2	Method 3	Method 4	**NFIM**	
"Russian"	1	35.62	24.32	22.82	18.64	18.65	15.56	16.06	17.26	**10.87**	43.15
	2	9.97	6.59	6.54	5.37	5.37	5.09	4.98	4.94	**4.13**	19.61
"German"	1	21.45	16.25	12.07	11.40	11.86	10.58	10.08	9.88	**6.97**	41.75
	2	11.78	8.25	6.97	6.61	6.62	6.03	6.00	5.66	**4.55**	24.40
"Ukrainian"	1	35.60	23.27	21.60	20.50	20.58	15.66	16.74	14.11	**8.65**	63.12
	2	1.22	0.72	0.75	0.66	0.66	0.61	0.63	0.57	**0.54**	5.56
"English"	1	29.85	18.37	17.77	14.17	14.28	12.78	11.71	12.22	**8.33**	40.58
	2	34.04	22.67	22.16	17.55	17.56	16.92	16.13	16.46	**13.40**	20.37

Note: The best results are highlighted.

12. Summary

When verifying theorems automatically, their validity can be proven by going through all constant cases. The first person to highlight this was Jacques Herbrand [32]. In the logic of predicates of the first order in far-away 1930, he proposed the procedure of verification based on the theorem which states: a range of disjuncts S is impossible when and only when there is finite impossible range of fundamental examples (*i.e.* constant cases) of disjuncts with S.

The proof of the theorem is called the answer to the question whether some formula B logically follows out of the stated range of formulae $f_1, f_2, \cdots, f_n$:

$f_1, f_2, \cdots, f_n \to B$ is the verification of general validity of the formula.

It is much easier to prove the unprovability of the formula:

$f_1, f_2, \cdots, f_n \to \neg B$—refutation procedure.

As for the question that is being considered in this article, it means that it is important to find such method of determination of combined conditional probability by unconditional and certain conditional ones which gives a better result than that offered in the non-force interaction theory. Moreover, it should be true for any texts.

The author did not manage to do this, despite doing his best. There is the last point, though. It seems that if from one text there are taken fragments $p^{\text{text 1}}(a_i/a_{i-1})$ and $p^{\text{text 1}}(a_i/a_{i+1})$, and the equivalent values of them are found in the other text

$$p^{\text{text 2}}(a_i/a_{i-1}) = p^{\text{text 1}}(a_i/a_{i-1});$$

$$p^{\text{text 2}}(a_i/a_{i+1}) = p^{\text{text 1}}(a_i/a_{i+1}),$$

then the value $p^{\text{text 1}}(a_i/a_{i-1}a_{i+1})$ will be closer to $p^{\text{text 2}}(a_i/a_{i-1}a_{i+1})$ than those received by listed methods. For example, if:

$$p^{\text{text 1}}(a_i/a_{i-1}) = p^{\text{text 2}}(a_i/a_{i-1}) = 0.7;$$

$$p^{\text{text 1}}(a_i/a_{i+1}) = p^{\text{text 2}}(a_i/a_{i+1}) = 0.3;$$

$$p^{\text{text 1}}(a_i/a_{i-1}a_{i+1}) = 0.8,$$

then

$$p^{\text{text 2}}(a_i/a_{i-1}a_{i+1}) \approx 0.8.$$

Otherwise, if the value of combined conditional probability is different for the same values of certain conditional probabilities, the question arises. Is it at all possible to find the method which orients itself at probabilities and will provide a better result than the non-force interaction method?

There was an experiment conducted. In "English" base, the input conditional probabilities are determined. In "Russian" base, the conditional probabilities equal to them are found. Certainly, finding all the probabilities in "English" base correspondent to each conditional probability of text fragments in "Russian" base failed (the deviation within 0.0005 was allowed). There was found K = 15,307 one-letter fragments where probabilities match.

By these fragments using least square method there was calculated the deviation dispersion of probability $p^{\text{English}}(a_i/a_{i-1}a_{i+1})$ from probability $p^{\text{Russian}}(a_i/a_{i-1}a_{i+1})$, and probability $p_9^{\text{Russian}}(a_i/a_{i-1}a_{i+1})$ from probability $p^{\text{Russian}}(a_i/a_{i-1}a_{i+1})$.

Here is the answer:

$$\frac{\sum_{i=1}^{K}\left(p^{\text{English}}(a_i/a_{i-1}a_{i+1}) - p^{\text{Russian}}(a_i/a_{i-1}a_{i+1})\right)^2}{K} \approx 0.0031873;$$

$$\frac{\sum_{i=1}^{K}\left(p_9^{\text{Russian}}(a_i/a_{i-1}a_{i+1}) - p^{\text{Russian}}(a_i/a_{i-1}a_{i+1})\right)^2}{K} \approx 0.0017463,$$

under the condition that

$$\left|p^{\text{English}}(a_i/a_{i-1}) - p^{\text{Russian}}(a_i/a_{i-1})\right| < 0.0005;$$

$$\left|p^{\text{English}}(a_i/a_{i+1}) - p^{\text{Russian}}(a_i/a_{i+1})\right| < 0.0005,$$

where K is the quantity of matches in the values of probabilities of "English" and

"Russian" bases; $p_9^{\text{Russian}}\left(a_i/a_{i-1}a_{i+1}\right)$ is estimate of combined conditional probability of sequence of text fragment a_i by the non-force interaction method in "Russian base"; $p^{\text{Russian}}\left(a_i/a_{i-1}a_{i+1}\right)$ is combined conditional probability of sequence of text fragment a_i in "Russian" base; $p^{\text{English}}\left(a_i/a_{i-1}a_{i+1}\right)$ is combined conditional probability of sequence of text fragment a_i in "English" base; $p^{\text{Russian}}\left(a_i/a_{i-1}\right)$ is conditional probability of sequence of text fragment a_i in "Russian" base if the previous fragment is a_{i-1}; $p^{\text{Russian}}\left(a_i/a_{i+1}\right)$ is conditional probability of sequence of text fragment a_i in "Russian" base if the following fragment is a_{i+1}; $p^{\text{English}}\left(a_i/a_{i-1}\right)$ is conditional probability of sequence of text fragment a_i in "English" base if the previous fragment is a_{i-1}; $p^{\text{English}}\left(a_i/a_{i+1}\right)$ is conditional probability of sequence of text fragment a_i in "English" base if the following fragment is a_{i+1}.

***Deviation dispersion of the probability calculated by the non-force interaction method is almost two times smaller than the dispersion of the probability deviation taken from the other text*!**

Therefore, the main conclusion of the experiments is the following: the method based on the non-force interaction theory is better when analysing natural language texts as it does not just operate probabilities, but rather reflects information interactions in a human brain while producing speech (letter combinations, words, sentences). Moreover, these interactions are described with the same formulae that are used in the description of mechanical movement and direct (contact) interaction of material objects if they are given information-probabilistic interpretation. In the author's opinion, this states that there is the correspondence of the processes of information interaction in a human brain when producing natural language texts (the second signal system) to the processes of interaction at the microlevel of the Nature, which speaks about the general validity of the received non-force interaction formulae.

13. Discussion

Is the information the basis of our Nature? Is it the foundation of all interactions? The results received make it very high that the probability of the fact that information also determines the processes of interaction on a physical level (interactions of different physical nature). Moreover, information processes in a human brain correspond to the non-force interaction model received from information-probabilistic interpretation of the laws of physics.

This direction is relevant and promising, open to work with for many scientists of different countries. Of course, the author is the advocate of the development in this direction. Furthermore, like nobody else, he is interested in that other scientists tried to refute this statement through other experiments. Then, if they fail to do so, this will be the confirmation of the non-force interaction theory (here is one more reference to Herbrand [32]).

14. Practical Implementation

If the consistent patterns in estimating combined conditional probability by the non-force interaction method are preserved in different subject fields, this creates a possibility to develop artificial intelligence systems, in which by the deviation of conditional probabilities from unconditional ones the value of the non-force influence of various factors will be calculated. Then, the total of these influences will determine the most probable reaction of the system. This will allow to create simple, cheap and… effective artificial intelligence systems in which accumulated statistic information will be in the basis of reflexes (development of the most probable reactions to external influences). Allow us to illustrate.

Let us assume that in the process of previous training the adequate reactions of the system to external influences were determined. The training process was in consistent exposure on the system showing adequate reactions:

Training sampling 1: $W_{k_1} \to R_{i_1}$;

Training sampling 2: $W_{k_2} \to R_{i_2}$;

$\vdots$

Training sampling j: $W_{k_j} \to R_{i_j}$;

$\vdots$

Training sampling *N*: $W_{k_N} \to R_{i_N}$,

where $W_{k_j} \subseteq W$ is a subrange of the factors of influence on the system at *j*-th step of training; $R_{i_j} \in R$ is an adequate reaction of the system at *j*-th step of training; *W* is the range of factors of influence; *R* is the range of reactions.

Let us assume that at the moment of time *t*, the system is exposed to the influences that are included in the subrange $w_s \in W_0$.

$$\forall R_i \in R, \forall w_s \in W_0 : p\left(R_i / w_s\right).$$

Of course, if in the system memory, the reaction to all this subrange of influences is determined,

$$\exists R_q \in R : p\left(R_q / W_0\right) = 1,$$

the task of decision making is trivial. The decision is reaction R_q. However, usually there are so many influences that it is impossible to accumulate statistics for all these combinations. In this case, the non-force interaction method can become useful. As it is possible to calculate the value of the influence on the reaction by deviation of $p\left(R_i / w_s\right)$ from $p\left(R_i\right)$. Then, the reaction with the highest combined conditional probability estimate $p_9\left(R_q / W_0\right)$ can be chosen and implemented (see Section 6).

As it was shown in the experiments and practice, the combined conditional probability estimate of the reaction calculated by the non-force interaction method allows to choose correct reactions in different subject fields in 99% of cases [4] [6] [30] [33]. At the moment, on the basis of the non-force interaction method the systems of reactive artificial intelligence machines that produce adequate reactions to the influences of the multitude of factors have been and are being developed. The author and his students have created the systems of: predicting the results of sport games, evaluation of investment proposals in development, access the databases using natural language, automatic abstracting of texts, automatic message forwarding, voice control of TV and phone, etc. [4]. The main advantage of these systems is not even the fact that they are more effective than others, but rather in the fact that the expenses on their development are minimum.

How do they work and why are they called the systems of a reactive type? The work started from the creation of the system of access to the database of the construction of Southern Ukrainian Nuclear Power Station using natural language [30]. It was developed the automated system which included almost all data necessary for construction: drawings (specifications), budget estimates, plans, scopes of conducted works, material and technical resources. Most of the workers had low level of computer skills (it was in 80s of the 20th century). Therefore, they were offered a system KET ("компилятор естественно-языковых текстов" in Russian, "natural language compiler" in English) which had single window where a user wrote their request in natural language. For example, "What scope of works was made last month in reactor department by subdivision PROM-1". There were standard reactions entered in the system. They were fulfilled by database management system КВАНТ-М:

- Tasks: planned scopes of works, planned cost of works, performance of works, need for resources;
- Construction objects: reactor department, generator hall, etc. (more than 100 objects);
- Performers (people responsible) (more than 100 organisations and subdivisions);
- And other.

During the training, the teacher entered a random sentence and chose corresponding reaction. In essence, the reflex to a request was developed. The reflex was created in the following way:

1) Input text was divided into fragments (from 2 to 10 symbols).

2) For each fragment, statistical probability of choice of each reaction (conditional probability) was calculated.

3) For each reaction, its statistical probability of choice (unconditional probability) was calculated.

4) The difference between conditional and unconditional probabilities for each reaction of each fragment was treated as a value of non-force (information) influence on this reaction by this fragment.

The reaction with the biggest sum of non-force influences from the user's request was chosen.

The use of the system showed its high reliability when processing users' requests. The probability of correct reaction for non-programming professionals (engineers, skilled workers, foremen) exceeded 95%. The most importantly, the system did not need to perform morphological, syntax, semantic analysis of the text as it is done by similar systems. The non-force interaction method is a really simple and reliable method of creation of the systems of natural language!

One more similar system was depicted in the publication [6]. This is the system of TV voice control. The principles, method and algorithm are the same as described in the system of access to databases. However, at the input it is not the text that is entered, but phonemes of a language. The probability of correct reaction in this system is close to 0.99.

The system of predicting the results of sport matches [1] works in a slightly different way. As an influenced object, there is a result of a match (win, draw, loss). As influencing objects there are various factors: the result of a previous match, what were the previous results of the matches between the same competitors, on whose field the game is, how many goals are scored and missed in previous matches. Factors like weather, referee, availability of a stronger team, etc. can be added. In this case, the unconditional probability of each result (win, draw, loss) of each team is chosen from the statistics, as well as conditional probabilities of these results, but only if the selected influence factors exist. The non-force influence, which is calculated as it is described in Subsection 2.3, characterises many factors that in total give a different value of result probability. Taking into account many factors gives probable result of a match. The statistics of predicting leading championships of European countries and matches of representative teams has been accumulated for 10 years. The probability of correct predicting of results in different championships varies from 0.55 to 0.65 (English championship is the most difficult to predict), and it reaches 0.7 for the matches of representative teams.

In the system of evaluation of investment proposals in development, the values of various parameters of projects (location, destination, cost, etc.) were calculated. This system is unique because in the process of experimental research it gave 100% match of parameter values to the ones given by experts [33].

15. Conclusions

The confidence of the author in the validity of the non-force interaction theory, its versatility, is based on computer experiments and practical implementation of the systems created with the use of the results receive in the non-force interaction theory [4] [6] [30] [33]. The theory was received from computer experiments in the basis of which it was the assignment of information content to objects (see **Figure 1**) and modelling of their mechanical movement and interaction during collision (the law of conservation of momentum) [4]. The information-probabilistic interpretation of mechanical movement was the result of these experiments. The next step of work on any theory is its experimental verification and practical implementation.

This work is dedicated to experimental verification of the general validity of the formulae of dealing with the information content of interacting objects, which were received from the information-probabilistic interpretation of mechanical movement. Specifically, its correspondence to the interaction processes happen in a human brain during producing natural language texts. All computer experiments, the results of which are provided in this article definitely show that the non-force interaction theory formulae allow to describe statistical consistent patterns in the texts of different languages more exactly than other methods selected for the experiments. In its turn, this allows to state that there is a high probability of **the interactions at both micro- and macro-levels of the Nature are informational (non-force) ones and are describes with the same formulae.**

However, it is also possible that it is not the information-probabilistic interpretation of mechanical movement that is primary, and it is not the one to be taken as the foundation of the research of natural language texts. It is possible that the existence of the systems in which the information lies in the basis of their life-sustaining activity, and their development, training and self-development, and their reflexes were the basis of the creation of "informational laws" of mechanical movement. Moreover, it is these laws that we research in **the computer simulation that we call the Universe** [1] [34] [35] [36] [37]…

Acknowledgements

Without the help of my friends, colleagues, students and family this article would never have been written. Firstly, I thank to my extremely talented and professional daughter, Yegorchenkova Natalia Yuriivna, Doctor of Science. She is both a science editor, assistant and professional advisor on the material of the article. Useful advice, constructive criticism and ideas which were aimed at improving the methodology of research are the input of my wife Olga Victorivna. All mathematical calculations were made under the supervision of a wonderful mathematician, Podchasova Tetiana Pavlivna, Doctor of Science. For advice on the same questions, I am really grateful to my colleagues, Scherba A. I., Candidate of Science, and Snytiuk Vitaliy Yevhenovych, Doctor of Science. Professional support in preparation of the article text was provided by my talented student and assistant Khlevna Yulia Leonidivna, Doctor of Science. Real support in my research and a person who in all situations backed me and my ideas up is Pavlenko Petro Mykolaiovych, Doctor of Science. For the professional translation of the article into English (and this is not the first time she performs the translation of my works) I thank to Mariana Kucherenko. I highly APPRECIATE everybody who made a contribution into this work!

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

[1] Bostrom, N. (2003) *Philosophical Quarterly*, **53**, 243-255. https://doi.org/10.1111/1467-9213.00309

[2] Wolfram, S. (2002) A New Kind of Science. Wolfram Media, Inc., Champaign. https://www.wolframscience.com/nks/

[3] Hooft, G. (2016) The Cellular Automaton Interpretation of Quantum Mechanics. Fundamental Theories of Physics, Vol. 185, Springer, Cham, 256 p. https://doi.org/10.1007/978-3-319-41285-6 https://link.springer.com/content/pdf/10.1007%2F978-3-319-41285-6.pdf

[4] Teslia, I.M. (2014) Non-Forceful Nature: Monograph. Chabanenko Yu.A., Ukraine, 176 p. https://er.chdtu.edu.ua/handle/ChSTU/2814

[5] Teslia, I. and Klapchenko, V. (2011) Probabilistic Interpretation of Mechanical motion. http://arxiv.org/find/all/1/all:+klapchenko/0/1/0/all/0/1

[6] Teslia, I., Pylypenko, V., Popovych, N. and Chornyy, O. (2014) The Non-Force Interaction Theory for Reflex System Creation with Application to TV Voice Control. 6*th International Conference on Agents and Artificial Intelligence* (ICAART 2014), Angers, 6-8 March 2014, 288-296.

[7] Landau, L.D. and Lifshitz, E.M. (1980) The Classical Theory of Fields. Course of Theoretical Physics Vol. 2, 4th Edition, Butterworth-Heinemann, Oxford.

[8] Feynman, R.P., Leighton, R.B. and Sands, M. (2005) The Feynman Lectures on Physics, Volume 1: Mainly Mechanics, Radiation, and Heat (Definitive ed.). Pearson Addison-Wesley, San Francisco.

[9] Alfredo, A. and Elizabeth, S. (2017) Wernicke's Area. *Reference Module in Neuroscience and Biobehavioral Psychology*, Elsevier, Amsterdam. https://www.researchgate.net/publication/312042389_Wernicke's_area

[10] Binder, J.R. (2015) *Neurology*, **85**, 2170-2175.

[11] Friederici, A. (2011) *Physiological Reviews*, **91**, 1357-1392. https://doi.org/10.1152/physrev.00006.2011 https://journals.physiology.org/doi/full/10.1152/physrev.00006.2011

[12] Hickok, G. (2009) *Physics of Life Reviews*, **6**, 121-143. https://doi.org/10.1016/j.plrev.2009.06.001 http://ncbi.nlm.nih.gov/pmc/articles/PMC2747108/

[13] Kuligowska, K., Kisielewicz, P. and Włodarz, A. (2018) Speech Synthesis Systems: Disadvantages and Limitations. *International Journal of Engineering and Technology* (*UAE*), **7**, 234-239.

[14] Schroeter, J. (2008) Basic Principles of Speech Synthesis. In: Benesty, J., Sondhi, M.M. and Huang, Y.A., Eds., *Springer Handbook of Speech Processing*, Springer, Berlin, Heidelberg, 413-428. https://doi.org/10.1007/978-3-540-49127-9_19 https://www.researchgate.net/publication/290619779_Basic_Principles_of_Speech_Synthesis

[15] Cheng, X.-Y. and Yan, P. (2011) Review of Modern Speech Synthesis. In: Hu, W., Ed., *Electronics and Signal Processing*, Vol. 97, Springer, Berlin, Heidelberg, 517-524. https://doi.org/10.1007/978-3-642-21697-8_65

[16] Mussabayev, R.R., Amirgaliyev, Y.N., Tairova, A.T., Mussabayev, T.R. and Koibagarov, K.C. (2016) The Technology for the Automatic Formation of the Personal Digital Voice Pattern. 2016 *IEEE* 10*th International Conference on Application of Information and Communication Technologies* (*AICT*), Baku, 12-14 October, 2016, 1-5. https://doi.org/10.1109/ICAICT.2016.7991733 https://ieeexplore.ieee.org/document/7991733

[17] Korkut, C., Haznedaroglu, A. and Arslan, L. (2020) Comparison of Deep Learning Methods for Spoken Language Identification. *SPECOM* 2020: *International Conference on Speech and Computer*, St. Petersburg, 7-9 October 2020, 223-231. https://doi.org/10.1007/978-3-030-60276-5_23 https://link.springer.com/chapter/10.1007/978-3-030-60276-5_23#citeas

[18] https://github.com/Yehorchenkov/data_for_paper_teslia

[19] http://ocw.mit.edu/ans7870/6/6.006/s08/lecturenotes/files/t8.shakespeare.txt

[20] https://modernlib.net/books/tolstoy_lev_nikolaevich/voyna_i_mir_tom_1/

[21] https://modernlib.net/books/tolstoy_lev_nikolaevich/voyna_i_mir_tom_2/

[22] https://all-the-books.ru/books/tolstoy-lev-voyna-i-mir-tom-3/

[23] https://all-the-books.ru/books/tolstoy-lev-voyna-i-mir-tom-4/

[24] http://originalbook.ru/faust-gyote-deutsch-faust-goethe/

[25] http://originalbook.ru/ecce-homo-f-nietzsche-deutsch/

[26] http://originalbook.ru/das-schlos-franz-kafka-deutsch/

[27] https://avidreaders.ru/book/kobzar.html

[28] https://royallib.com/book/kostenko_lna/zbrka_vrshv.html

[29] Teslia, I. (n.d.) Personal Site. http://teslia.kyiv.ua/?page_id=55

[30] Teslia, I. (1998) Reactive System of Processing Natural Language Texts in Automated Command and Control System of the Construction of Complex Power plants. *Radioelectronics and Information Science*, No. 4, 52-55.

[31] Lebedev, Y., Livinska, G., Rozor, I. and Sharapov, M. (2016) Mathematical Statistics: Starter Guide. PPC "Kyiv University", Kyiv, 160 p. (Ukrainian) http://applstat.univ.kiev.ua/ukr/docs/materials/matstat.pdf

[32] Louis Laurière, J. (1991) Problem-Solving and Artificial Intelligence. Mir, Moskow, 568 p. (Russian) http://library.kpi.kharkov.ua/vustavki/Lingv/38.pdf

[33] Teslia, I., Kayuk, P. and Chernova, M. (2011) Formation and Analysis of Decision Making to Evaluate Investments in Development Projects. *Management of Complex system Development*, No. 7, 60-62.

[34] Bostrom, N. (2005) *Philosophical Quarterly*, **55**, 90-97. https://doi.org/10.1111/j.0031-8094.2005.00387.x

[35] Brueckner, A. (2008) The Simulation Argument Again. *Analysis*, **68**, 224-226. https://doi.org/10.1093/analys/68.3.224

[36] Campbell, T., Owhadi, H., Sauvageau, J. and Watkinson, D. (2017) On Testing the Simulation Hypothesis. http://www.ijqf.org/wps/wp-content/uploads/2017/03/IJQF-3888.pdf

[37] Fan, R., Wang, J.-Y. and Li, H. (2008) Discussion on Simulation Application Theory. 2008 *Asia Simulation Conference*: 7*th International Conference on System Simulation and Scientific Computing*, Beijing, 10-12 October 2008, 363-367.