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RICHARDSON'S MULTILATERAL MILITARY EXPENDITURE MODEL AUGMENTATION VIA SENTIMENT ANALYSIS OF NEWS DATA IN THE FRAMEWORK OF COMPLEXITY ECONOMICS[1]

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Complexity economics incorporates factors that are not accounted for in classical economic thought. With this paper, we intend to demonstrate the potential of using the complexity economics frame of reference by revisiting an existing model of the past, especially one that has been proven to be effective and, most importantly, could utilize the recent developments in advanced analytics as a tool to address a more realistic social milieu. We propose the introduction of more complex dynamics into an already existing model by using Deep-Learning-based NLP analysis of large news article data to fill in the action-reaction matrix for Richardson's multilateral arms race model. By introducing said complex dynamics we also opened a discussion about the effect that media has on democratic societies' military spending and concluded at the first level of analysis that media has a significant influence on the electorates' decision-making of democratic nations in the matter of arms race and defense budgets. Also, we were able to demonstrate the final form of the augmented multilateral arms race model and its predictive capacity. We hope that our findings will encourage the use of advanced analytics in the framework of complexity analysis and improve the existing models' performance via big data insights.

Keywords: *complexity economics, multilateral arms race model, sentiment analysis, military spending*

Introduction

Since the beginning of the 20th century, economic thought has developed in strides. Certain metrics for understanding the state of the economy and its potential for growth and development have been tested and morphed into becoming established macro/microeconomic indicators used in a prolific manner across the world and by many states and corporations as well as by most if not all, leading international financial institutions. At first glance, one might think that these indicators are good enough reflections of various aspects of the economy, and it might be considered completely harmless if not useful to calculate these indicators and use them in the general analysis of the state of a given economy. In practice, though, we end up in a situation where crucial policies are directed and evaluated on the basis of these and other metrics which are the result of neoclassical understanding and stance on economic theory. In his milestone paper on the foundations of complexity economics, Brian Arthur put forward several arguments that point out the fundamental problem of the neoclassical school of thought which in essence is the fact that these are just theories

[1] The paper is the extension of the abstract submitted to the conference of Armenian Economic Association held in Yerevan in 2023.

that have been formulated using the abstraction method[2]. Via abstracting from the complex reality, the neoclassical school of economics has formulated elegant and functional theories, which in practice lead to devastating results and, simply put, do not work.

Similar work had been done by Richardson on the matter of modeling the multilateral arms race and military spending during the Cold War[3]. Richardson's approach to quantifying various complex factors and using them in his proposed model is, in fact, a way of successfully modeling complex phenomena into a predictive and understandable framework.

Thus, the primary research objective of this study is to demonstrate a complexity-introducing approach with the existing model's extension which includes large amounts of data processing, namely news article sentiment analysis.

The research questions, objectives, and hypothesis

Primary research question: Is it possible to extend Richardson's model with the inclusion of behavioral aspects into the differential equation for the modeling of defense spending?

Secondary research question: Do the insights gained through the injection of the NLP analysis improve the model's performance in any significant way?

Main objective: Derive a data-driven framework for satisfying the primary research question.

Secondary objective: Summarize the net result of using such a technique to assess the performance of the enhanced model for the secondary research question.

H0_major: It is possible to extend Richardson's model with behavioral aspects of news sentiment analysis.

H0_minor: The extended model will give more insights and improve the efficiency of the model substantially.

The demand for exploring the relationship between military expenditure and public sentiment shaped by media

The notion that the media follows foreign policy is self-evident, but the reverse relationship: the media's effect on the foreign policy of a given country is in many cases neglected. In the following section of the paper, we will explore that relationship by studying the related work in the field. Addressing this issue will provide us with some understanding of the biases and limitations in the approach we have taken and will point out some future research areas.

In his famous paper about the so-called "CNN effect" after reviewing the matter with five cases Piers R. concluded that although there appears to be a mutual relationship between the reported cases and actual policy, the matter of which side has a decisive impact should be discussed in three dimensions:

- the actual analysis of the impact of media as opposed to other factors,
- the explanation of cases when the media pressured action and policy did not follow,

[2] **Arthur, W.B.**, 2021. Foundations of complexity economics. *Nature Reviews Physics*, *3*(2), pp.136-145. DOI: 10.1038/s42254-020-00273-3

[3] **Ward, M.D.**, 2020. Back to the Future: Richardson's Multilateral Arms Race Model. *Lewis Fry Richardson: His Intellectual Legacy and Influence in the Social Sciences*, *27*, pp.57-71. DOI: 10.1007/978-3-030-31589-4

● the interests of the parties that control the media[4].

Another viewpoint that complements the dimensions discussed above was brought forward by Justin L. He expanded on the third dimension put forward by Piers and discussed the supporting role of media in terms of interventional policies with an emphasis on certain common interests between the military-industrial complex and the media[5].

Nevertheless, the extended model that we propose here does not involve any significant consideration of the mutual relationship described above. Though we consider our data-driven approach being superior to that of the manual approach taken by Richardson; especially given the fact that we take millions of articles from various sources, we still believe that this area of research needs more deliberate attention.

Modeling of multilateral military expenditure

In his review of the multilateral arms race model suggested by L.F. Richardson Ward M.D. outlined the two basic innovations in social sciences brought by Richardson:

● the power of mathematics for understanding complex social systems,

● the importance of understanding the interdependence of various phenomena that are usually studied separately[6].

With the aim of modeling the multilateral arms race during the Cold War Richardson developed an approach that consists of two parts.

First, he calculated the so-called "action-reaction" or "cause-consequence" matrix <u>not following any statistical procedure</u> but mostly relying on his analysis of the news reporting and radio.

Second, the matrix mentioned above was used in a simple differential equation that models the relationship among countries' military spending (eq. 1):

$$\frac{dx_i}{dt} = g_i + \sum_{j=1}^{j=n} k_{ij} x_j \qquad \forall\, i \in \{1,2,..,n\} \quad eq.1$$

Where x_i is the military spending for nation *i*, and k_{ij} has the action-reaction coefficients off the diagonal and the economic constraints on the diagonal, and g_i portrays the hostility terms[6].

Though the model proved to be extremely insightful, the primary weakness of its implementation lay in the fact that the key component of the model, i.e. the "action-reaction" matrix, was filled using a <u>subjective procedure</u>. In fact, no person can be deemed unbiased on the matter of analyzing news reporting as B.H. Fortner and W.A. Hank demonstrated in their research underlining a reader's three crucial biases: ego-involvement, prior knowledge, and the purpose of reading[7].

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[4] **Robinson, P.**, 1999. The CNN effect: can the news media drive foreign policy?. *Review of international studies*, *25*(2), pp.301-309. DOI: 10.1017/S0260210599003010

[5] **Lewis, J.**, 2008. The role of the media in boosting military spending. *Media, War & Conflict*, *1*(1), pp.108-117. DOI: 10.1177/1750635207087631

[6] **Ward, M.D.**, 2020. Back to the Future: Richardson's Multilateral Arms Race Model. *Lewis Fry Richardson: His Intellectual Legacy and Influence in the Social Sciences*, *27*, pp.57-71. DOI: 10.1007/978-3-030-31589-4

[7] **Fortner, B.H. and Henk, W.A.**, 1990. Effects of issue-related attitude on readers' comprehension and judgments of unbiased text. *Literacy Research and Instruction*, *30*(2), pp.1-16. DOI: 10.1080/19388079109558038

Moreover, even if we assumed that the analysis of the person carrying it was accurate, the second problem that would soon arise would be about replicating their results or even continuing the use of the model after their demise.

Thus, we intend to ameliorate the discussed issues with a matrix completion process involving modern NLP approaches which could help us to standardize, scale, and replicate the procedure of analyzing news data for Richardson's multilateral arms race model. In short, the NLP approach that we have chosen will fill in sentiment values within the k matrix for the chosen 11 countries. Next, we will discuss more in detail what exactly we expect to accomplish and how.

Natural language processing augmentation to the model

The case of using natural language processing (NLP) in the process of the "action-reaction" matrix completion seems self-evident given the points discussed above. Therefore, we would like to specify here which specific NLP approach we have chosen to use and why.

In the science of NLP, more specifically in the objective of deriving sentiments (which is our use-case of NLP), it is common to approach the analysis of text data in three dimensions: document, sentence, and entity or aspect[8]. As our analysis involves finding out specific sentiments from country A towards country B and vice versa, the obvious choice for us will be to approach the task with aspect-based sentiment analysis (ABSA). Here we aim to extract the so-called aspect sentiment triplets, first described by Lu X. et al[9]. Let's apply this technique to an example:

The US Embassy warned its citizens to urgently leave Russia.

Here we can see two aspects of interest: the US and Russia. Their interaction is captured via the word "urgently leave", thus we expect a simple ABSA algorithm to return a triplet consisting of the following: (US, urgently leave, negative); (Russia, urgently leave, neutral).

Heng Y. et al. came up with an open-source implementation of such an NLP solution called "PyABSA", which is implemented in the Python programming language[10]. It is important to note that there are some other implementations of aspect-based sentiment analysis. That said we chose to use the one mentioned above due to its robust performance on general benchmarks and for the fact that it is open source. Nevertheless, we would like to acknowledge that other implementations of such an algorithm would produce slightly different results due to model and data characteristics and the general probabilistic nature of ML algorithms.

Last but not least, before feeding the model the articles we summarized them using the NLP library "spacy" with our custom function, which transforms the article text into a coherent and meaningful representation using 10% of the initial tokens present in the article. This way we not only speed up the computation process but also make sure that the essence of a given article is analyzed as opposed to the peripheral aspects of the text.

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[8] **Do, H.H., Prasad, P.W., Maag, A. and Alsadoon, A.**, 2019. Deep learning for aspect-based sentiment analysis: a comparative review. *Expert systems with applications*, *118*, pp.272-299. DOI: 10.1016/j.eswa.2018.10.003

[9] **Xu, L., Chia, Y.K. and Bing, L.**, 2021. Learning span-level interactions for aspect sentiment triplet extraction. *arXiv preprint arXiv:2107.12214*.

[10] **Yang, H. and Li, K.**, 2022. PyABSA: Open Framework for Aspect-based Sentiment Analysis. *arXiv preprint arXiv:2208.01368*.

The data

We used an open-source dataset created by Andrew Thompson containing over 2 million articles from the years 2016 to 2020 scraped from various popular media websites[11]. The features for each row are the following:

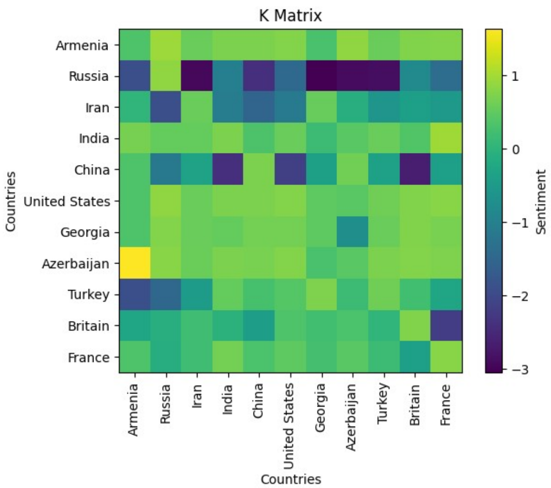
- date (str): Datetime of article publication.
- year (int): Year of article publication.
- month (float): Month of article publication.
- day (int): Day of article publication.
- author (str): Article author, if available. A comma separates multiple authors.
- title (str): Article title.
- article (str): Article text, without paragraph breaks.
- url (str): Article URL.
- section (str): Section of the publication in which the article appeared, if applicable.
- publication (str): Name of the article publication.

During our analysis we only used the date, title, and article, ignoring section and other columns so that we do not limit our research to the publications that have been assigned certain sections by mistake or miss having the section/topic information altogether. It is also worth mentioning that certain country pairs had substantially larger quantities of referring articles than others. Nevertheless, the core objective of this analysis revolves around bilateral relations among all countries, thus making the disbalance of data merely a matter of intensity.

It is also of crucial importance to note that there are certain innate biases associated with the data as it consists of mostly Western news articles and further research can be done to evaluate the impact of using such data.

Multilateral effect analysis of the military expenditure

For 2016 we calculated the sentiment values for the abovementioned 11 countries. The resulting sentiment values were scaled via the formula: z = (x - u) / s, where u is the sample mean, s is the standard deviation of the samples, and x is a given sample (for exact values see Appendix 1).

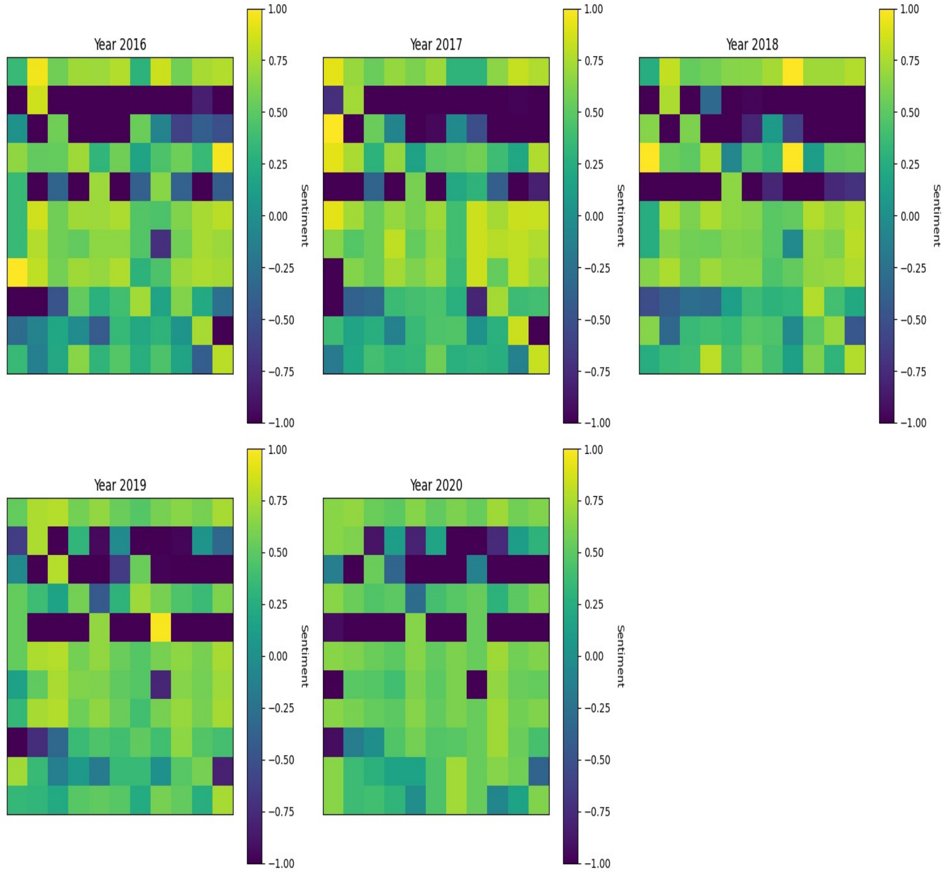


Plot 1: 2016 K-matrix heatmap (standard scaled)

[11] The link to the dataset: https://components.one/datasets/all-the-news-2-news-articles-dataset

As we can see from the heatmap (Plot 1) of the standard scaled K-matrix, e.g. Armenia's sentiment was predominantly positive towards Russia, but Russia's sentiment was significantly more hostile towards Armenia. It goes without saying that some interactions are easy to interpret, such as the hostility from China towards India, the US, and Britain. Nevertheless, some interactions are hard to interpret at first glance, e.g. Azerbaijan's positive sentiment towards Armenia. This and other such cases might be a result of certain countries' usage of media as a tool to portray themselves in a better light or a result of the lack of robustness of our method or a combination of both. That said, the former point regarding the use of media as a way of promoting a well-rounded image of a nation is well known in academic circles[12], as discussed by Fürsich E., and has the potential of skewing some of the results in such big-data analysis-driven models; what appears to be left to do is to leave this point for further research and accept such factors as potential impediments towards finding a much more effective and robust model augmentation technique.

In addition, let's see the change in the interactions across time by examining the heatmaps for years 2016 up to and including 2020 (Plot 2).

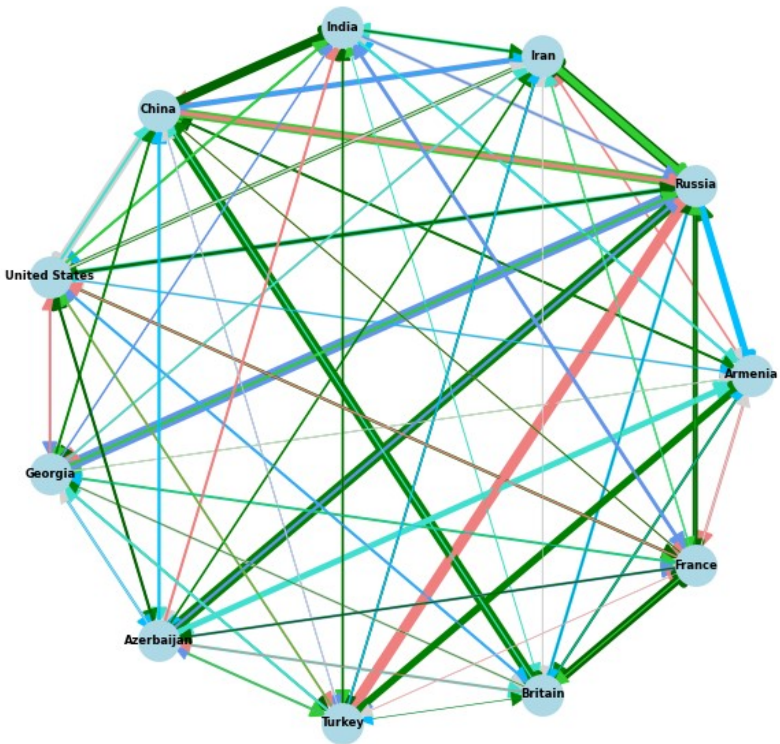


Plot 2: 2016-2020 K-matrix heatmaps (standard scaled)

[12] **Fürsich, E.**, 2010. Media and the representation of Others. *International social science journal*, *61*(199), pp.113-130. DOI: 10.1111/j.1468-2451.2010.01751.x

We can clearly see dynamic changes happening here in the relations between Turkey and Iran, Armenia and India, France and Iran, etc.

The representation of the matrix in the form of a heatmap gives us insight into the various interactions between countries, but to further understand the overall picture of the interaction we can interpret the matrix via a directed graph interaction plot (Plot 3). Here we can see the weighted interactions between countries and get a glimpse of which country dominates the other in terms of sentiment values, which, to some degree, reflects the cause-consequence relationship for increasing or decreasing military spending for a given country.



Plot 3: 2016 K-matrix visualization as a weighted graph network (standard scaled)

What this plot reveals to us is of crucial importance. We have chosen very particular countries to conduct the analysis on. It is obvious that in this cluster of 11 countries Russia and China dominate the sentiment interaction arena which can be explained by the fact that 3 of the chosen countries are ex-Soviet, and 8 lie fully or predominantly in Asia (for seeing the dynamics across years see Appendix 2).

We will later explore these relations and expand on various factors that play within the dynamics of the arms race and foreign politics. For now, let's return to our discussion of Richardson's model and complete the task described above. The seemingly missing part of the equation is the hostility terms, which, by the nature of the construction of our k-matrices, we can derive from those, i.e. by taking the average of the k-matrix values for each country.

By filling in all the constants and taking as initial conditions the 2015 military expenditures of the 11 counties from the World Bank database[13], we were able to calculate the standardized projections for military expenditure for 2016 using the Python library *scipy.integrate* for solving the differential equation (Table 1).

Countries	*projected*	*actual*
Armenia	-5.52%	-3.57%
Russia	-1.81%	4.25%
Iran	-4.95%	15.82%
India	-2.66%	10.41%
China	5.52%	1.02%
United States	30.15%	0.95%
Georgia	-5.53%	5.24%
Azerbaijan	-5.39%	-51.84%
Turkey	-4.67%	13.78%
Britain	-2.17%	-11.11%
France	-2.98%	3.77%

Table 1: The project vs real growth of military expenditure for 2016

Here we can see that for 5 countries out of 11, we were able to predict the right trend, while for the most part, we were able to be in the realistic intervals of change, with the exceptions of the USA and Azerbaijan.

Conclusions

In conclusion, both our hypotheses were confirmed. We were, indeed, successful in the objective of extending Richardson's Multilateral Arms Race model (H0), and given all the insights gained from the k-matrices we can say undoubtedly that more insights have been gained through such an approach while boosting the model's efficiency, replicability, and robustness. Further research might involve looking deeper into the relationship among media, the electorate, and budgeting decision-making regarding defense spending. Also, the limitations of data quality control and quantity should be taken into consideration in future research as the innate biases of the data and the data collection process were not in the scope of this paper though they are essential factors for the results of the computation.

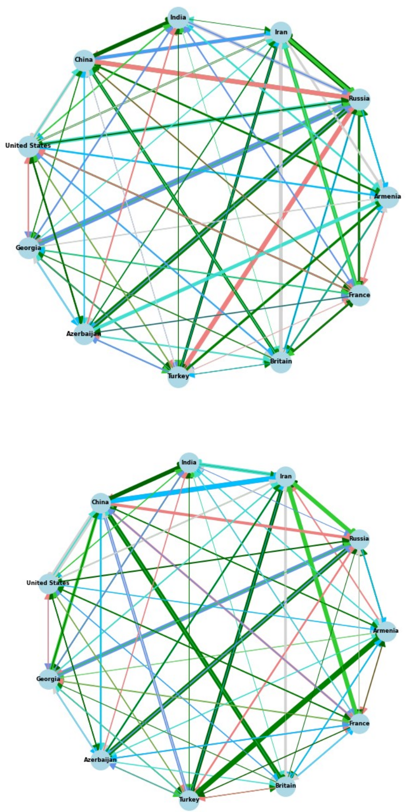
[13] See: https://data.worldbank.org/

Appendix 1

	Armenia	Russia	Iran	India	China	US	Georgia	Az.	Turkey	Britain	France
Armenia	0.35	0.95	0.57	0.71	0.71	0.77	0.3	0.85	0.57	0.74	0.77
Russia	-1.9	0.85	-2.94	-1.03	-2.42	-1.44	-3.04	-2.9	-2.87	-0.83	-1.38
Iran	0.03	-1.9	0.57	-1.05	-1.52	-1.13	0.55	-0.11	-0.61	-0.4	-0.52
India	0.67	0.52	0.53	0.71	0.32	0.57	0.17	0.44	0.56	0.36	0.97
China	0.35	-1.16	-0.36	-2.42	0.71	-2.15	-0.39	0.65	-0.37	-2.66	-0.41
USA	0.35	0.85	0.57	0.71	0.71	0.76	0.47	0.44	0.62	0.74	0.79
Georgia	0.35	0.77	0.57	0.52	0.66	0.66	0.47	-0.72	0.57	0.74	0.7
Azerbaijan	1.63	0.81	0.58	0.71	0.68	0.76	0.3	0.44	0.7	0.76	0.73
Turkey	-1.9	-1.46	-0.48	0.52	0.27	0.4	0.72	0.17	0.62	0.22	-0.27
Britain	-0.29	-0.11	0.2	-0.03	-0.42	0.34	0.21	0.3	0.03	0.74	-2.19
France	0.35	-0.14	0.21	0.65	0.31	0.47	0.25	0.44	0.17	-0.4	0.79

The action-reaction matrix for 2016 after applying standard scaling.

Appendix 2



K-matrix visualization as weighted graph networks (standard scaled) from 2017 to 2020 in left-right order.

ՄՀԵՐ ՎԱՐԴԱՆՅԱՆ – *Ռիչարդսոնի բազմակողմ ռազմական ծախսերի մոդելի ընդլայնումը նորությունների տվյալների վերլուծության միջոցով բարդության տնտեսագիտության շրջանակներում* – Բարդության տնտեսագիտությունը հաշվի է առնում գործոններ, որոնք անտեսվում են դասական տնտեսագիտական մտքում: Հոդվածում ցույց տալ է տրվում բարդության տնտեսագիտության հիման շրջանակի օգտագործման ներուժը՝ վերանայելով գոյություն ունեցող մի մոդել, որի արդյունավետությունը ապացուցված է և ամենակարևորը՝ այն կարող է օգտագործել առաջադեմ վերլուծական մեթոդների վերջին ձեռքբերումները որպես գործիք՝ ավելի իրատեսական սոցիալական միջավայրին անդրադառնալու համար:

Առաջարկվում է ավելի բարդ դինամիկայի ներմուծում արդեն գոյություն ունեցող մոդելում՝ օգտագործելով խորը ուսուցման վրա հիմնված բնական լեզվի մշակում պարունակող վերլուծությունը խոշոր նորությունների հոդվածների տվյալների՝ Ռիչարդսոնի բազմակողմ սպառազինությունների մրցավազքի մոդելի գործողություն-արձագանք մատրիցը լրացնելու համար: Ներկայացնելով նշված բարդ դինամիկան՝ քննարկվում է ԶԼՄ-ների ազդեցությունը ժողովրդավարական հասարակությունների ռազմական ծախսերի վրա և վերլուծության առաջին մակարդակում եզրակացուն է արվել, որ լրատվամիջոցները էական ազդեցություն ունեն ժողովրդավարական երկրների ընտրողների որոշումների կայացման վրա սպառազինությունների մրցավազքի և պաշտպանության բյուջեների ձևավորման հարցում: Բացի այդ, ներկայացվել են սպառազինությունների մրցավազքի ընդլայնված բազմակողմ մոդելի վերջնական ձևը և դրա կանխատեսման կարողությունը:

Բանալի բառեր – *բարդության տնտեսագիտություն, բազմակողմ սպառազինությունների մրցավազքի մոդել, տրամադրությունների վերլուծություն, ռազմական ծախսեր*

МГЕР ВАРДАНЯН – ***Расширение многосторонней модели военных расходов Ричардсона с помощью анализа настроений новостных данных в рамках экономики сложности.*** **–** Экономика сложности включает в себя факторы, которые не учитываются в классической экономической мысли. В этой статье мы намерены продемонстрировать потенциал использования системы отсчета экономики сложности путем пересмотра существующей модели прошлого, особенно той, которая доказала свою эффективность и, что наиболее важно, может использовать последние разработки в области расширенной аналитики в качестве основы инструмент для обращения к более реалистичной социальной среде. Мы предлагаем ввести более сложную динамику в уже существующую модель с помощью обработки естественного языка на основе глубокого обучения данных больших новостных статей, чтобы заполнить матрицу действия-реакции для многосторонней модели гонки вооружений Ричардсона. Вводя указанную сложную динамику, мы также открыли дискуссию о влиянии СМИ на военные расходы демократических обществ и пришли к выводу на первом уровне анализа, что СМИ оказывают значительное влияние на принятие решений избирателями демократических стран по вопросам гонка вооружений и оборонный бюджет. Кроме того, нам удалось продемонстрировать окончательную форму расширенной модели многосторонней гонки вооружений и ее предсказательную способность. Мы надеемся, что наши результаты будут способствовать использованию расширенной аналитики в рамках анализа сложности и повысят производительность существующих моделей за счет анализа больших данных.

Ключевые слова: *экономика сложности, многосторонняя модель гонки вооружений, анализ тональности текста, военные расходы*