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Magnetic Declination Statistics (Dusheti 1935-1989) and Deep Self-Learning Model

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ABSTARCT

Nowadays, there are many new instruments available for studying the parameters of the Earth's magnetic field with higher precision and more discretization. Moreover, data processing techniques have been developing on strong mathematical basis. The paper presents a rather long-term (1935 - 1950, total 19332 records) data of Dusheti Observatory on the statistics of magnetic declination (1) and considers the possibilities of so called machine learning (ML), a widespread method nowadays. It gives hypotheses to prove certain hidden regularities and periodicity of some geomagnetic parameters and determines so called "storages" of high statistical reliability, which are the etalon samples we use to build attribution function by use of so called Adam Deep Learning network (2).

Key words: *Earth's magnetic field, Adam Deep Learning network.*

Preamble

It is required to carry out certain statistical works in order to study a kind of long-term statistics as described in this work. We decided it was necessary to build standard variation series for magnetic declinations on the basis of months and years. Namely, it is important to make time period observations on variation series, also on separate series for 2σ and 3σ (3) parts. These two series turn out to be interesting in the annual point of view. It is highly essential to identify the density distribution of the statistical data in these clusters and whether they show any distribution regularities or behavior in dynamics.

Obviously, there is always an objectivity degree problem (equipment defects, etc.) in data. Consequently, it is required to exclude subjective statistics and there are numerous techniques for that. Nowadays, softwares with filtration tasks have been highly developed among computer technologies. Our data have undergone strict filtration processes. Of course, main informative anomalies have been preserved that is definitely significant.

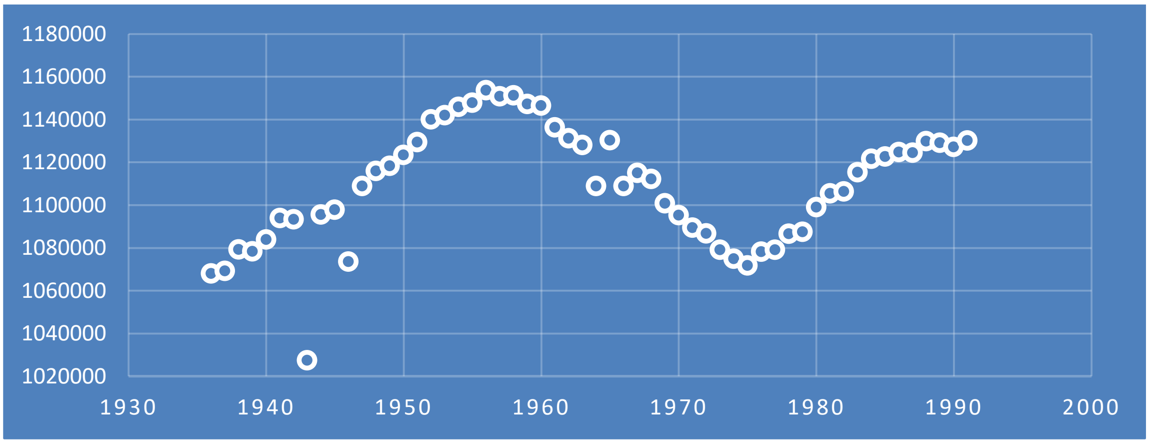

Fig. 1. Dynamics of average annual magnetic declination values (1936 - 1991).

The average annual values in *Figure 1* have periodic and regular structure. There is an exception of the Dusheti Observatory data of 1941-1942 and 1964-1966 in the average annual value point of view. These two episodes are conceivable, though, due to quite objective reasons, they might be a result of strong influence of artificial anomaly nearby the equipment location. We may conclude that, according to the figure, the average annual values have approximately 40-year cycles. Additionally, so called wave behavior has been revealed.

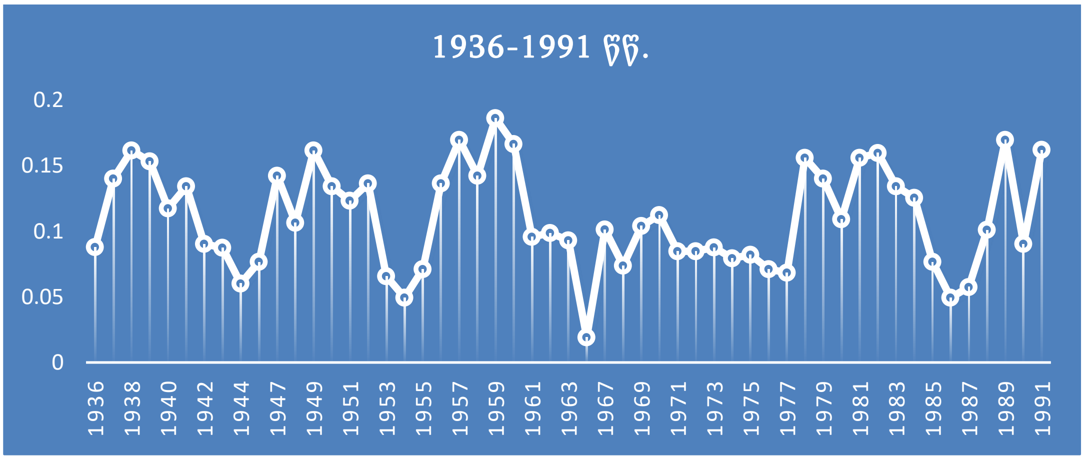

Fig. 2. Quantitative time period analysis of 2σ order anomalies of the magnetic field declination during 1936-1991.

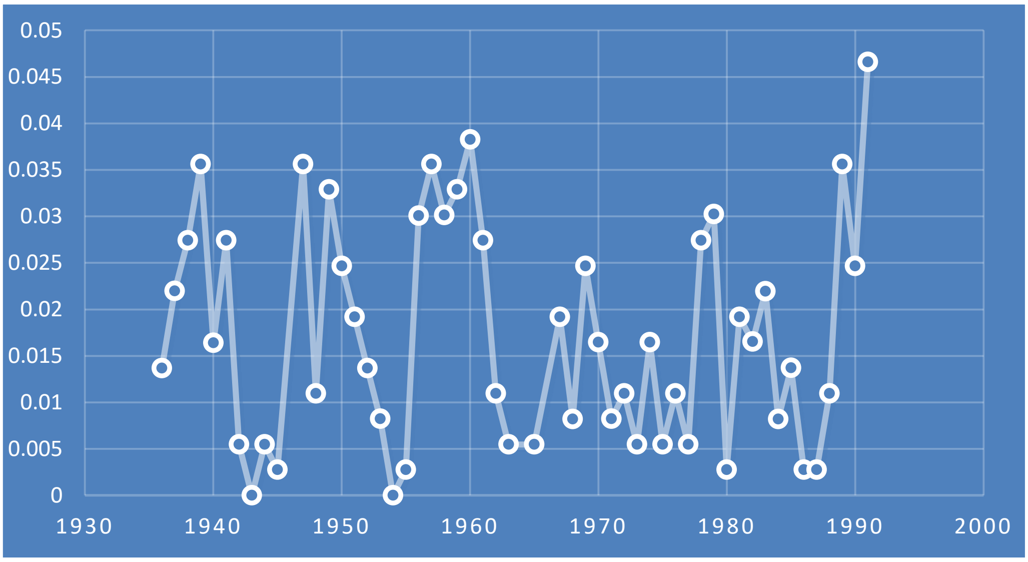

Fig. 3. Quantitative time period analysis of 3σ order anomalies of the magnetic field declination during 1936-1991.

Figure 2 shows shares of more than 2σ anomalies in a concrete year among the whole annual data. In 1936, for example, among the whole data the anomalies were declined from average value by more than 2σ altogether in 8% cases. Like this, in 1959 the number of such anomalies makes only 20% of the annual data. The issue of anomaly measurements according to the distinguished years is quite informative by frequency calculations in this figure.

Figure 3 shows shares of more than 3σ anomalies in a concrete year among the whole annual data. Here, statistical stability is under doubt and verification of statistical hypotheses of strong anomaly zones is prevented as far as their reliability is doubtful. There a question arises: why? It is due their limited involvement with all the data. However, from 1936 to 1960 their share is more than in 1960-1985, whereas at the end of the 80-s of the past century, processes similar to the ones in 1936-1960 take place.

From *Figures 1, 2* and *3* we may conclude that there is an alternation of rise (more dynamics) and fall in the magnetic declination. We are interested in the proceeding of the data till now. Does the magnetic declination parameter maintain its characteristics? Additionally, it is noteworthy to mention that there an alternation of average declination takes place from year to year, an average of so called *Up* and an average of so called *Down*. For example, so called Up-s and Down-s (frequent alternations of rise and fall) according to months must be a potential to build a good forecasting model.

If we bring in the following marks for our magnetic declination statistics:

$$X_{i\ ,} \qquad where\ (i\ is\ changed\ 1{:}\,19332\ )$$

we can build the following matrix:

Let us make components from previous 30 data in time for each *i* member. Our task is to find such F function, which will find links between any X_i and previous 30 records.

In this way we receive:

$$F(X_i, X_{i+1}, X_{i+2} \dots X_{i+30}) \cong X_{i+31} \qquad (1)$$

The whole machine learning theory considers optimization of *F*, which uses different algorithms. In this paper we will consider Adam Optimization Algorithm for Deep Learning (1).

The normalized learning sampling for Formula (1) in the form of a real table is given as follows:

X1	**X2**	**X3**	**..**	**..**	**..**	**X29**	**X30**	**X(31)**
2899	2898	2893	..	..	..	2922	2925	2921
2898	2893	2898	..	..	..	2925	2921	2920
2893	2898	2902	..	..	..	2921	2920	2917
2898	2902	2908	..	..	..	2920	2917	2917
2902	2908	2918	..	..	..	2917	2917	2920
2908	2918	2930	..	..	..	2917	2920	2913
..	..	..	..	..	..	..	..	..
2917	2911	2912	..	..	..	2925	2925	2925
2911	2912	2910	..	..	..	2925	2925	2919

Finally, we received a learning sampling with 30 inputs and one output.

A significant detail in the algorithm is the one, which can find links between each reading and its predecessor 30 data. In this case we will construct such a model, which will enable us to make an optimal prognosis by every 30 predecessor reading by means of Adam network.

$$w_{t+1} = (1-\lambda)w_t - \eta \nabla f_t(w_t) \quad (2)$$

As we know, in Adam algorithm, optimization of (1) is a solution to equation (2) for each necessary iteration (usually, there are 1000 iterations) for weight sampling, where λ is a parameter guiding the weight drop. Of course, here we have L2 regularization for decreasing unjustified weights, which is based on so called penalty principle, finally, on search function modification to have L2 -norm weight vector (4).

Table 1. Matrix of confusion (clarity) of the prognosis by 30-day predecessors of 1936-1991 magnetic field declination.

Target output:	Network output:									
	<2851	2851 .. 2887.6	2887.6 .. 2924.2	2924.2 .. 2960.8	2960.8 .. 2997.4	2997.4 .. 3034	3034 .. 3070.6	3070.6 .. 3107.2	3107.2 .. 3143.8	3143.8 .. 3180.4
2851 .. 2887.6	0	0	2	1	0	0	0	0	0	0
2887.6 .. 2924.2	0	0	65	158	1	0	0	0	0	0
2924.2 .. 2960.8	0	0	0	1810	70	0	0	0	0	0
2960.8 .. 2997.4	0	0	0	197	1813	37	0	0	0	0
2997.4 .. 3034	0	0	0	2	444	1224	73	0	0	0
3034 .. 3070.6	0	0	0	0	1	100	1598	142	0	0
3070.6 .. 3107.2	0	0	0	0	1	3	90	2624	165	2
3107.2 .. 3143.8	0	0	0	0	0	0	0	105	1432	39
3143.8 .. 3180.4	0	0	0	0	0	0	0	2	401	494
3180.4 .. 3217	0	0	0	0	0	0	0	1	3	25

Table 1 shows the qualitative assessment of the obtained prognostic model according to their interval (cluster) distribution. More exactly, here we have real and false coincidences of prognostic and real data, which are expressed quantitatively and by clusters.

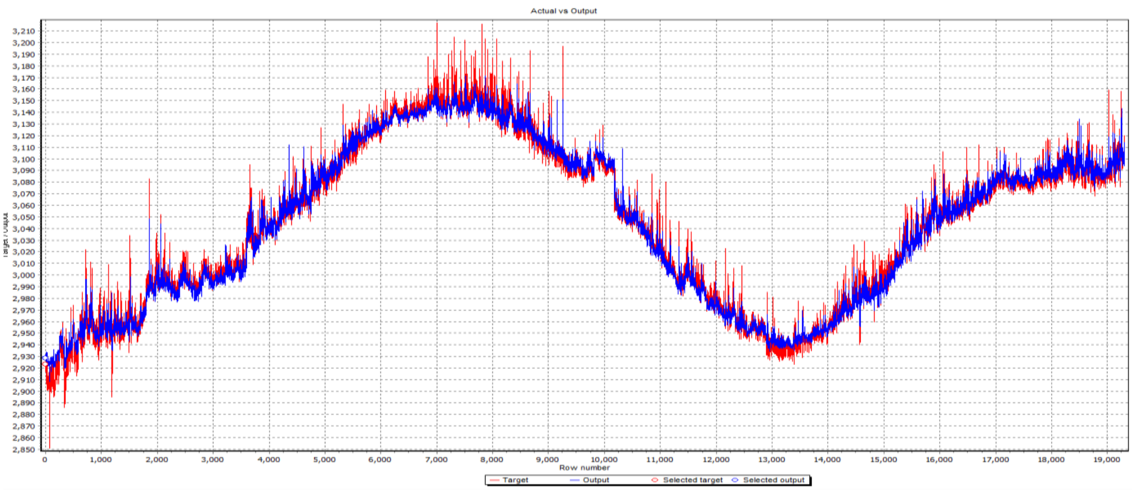

Fig. 4. Scheme of the prognosis by 30-day predecessors of 1936-1991 magnetic field declination.

Figure 4 clearly shows the compatibility between learning sampling and prognostic model. The real data are given in red colour and the prognostic values are shown in blue. It is obvious that the values of the strong anomalies, which took place in 1940-1950, are not reliable. However, taking into account these anomalies, the model revealed similar strong anomalies of the same order more accurately at the end of 1980-s. Finally, we have following characteristics for the constructed model:

	Target	Output	AE	ARE
Mean:	3042.505371	3041.840249	5.740834	0.001887
Std Dev:	68.173232	67.271728	5.886604	0.001927
Min:	2851	2908.161365	0.000849	2.71E-07
Max:	3217	3171.404207	101.941242	0.033066

Correlation: 0.992766

R-squared: 0.98506

The obtained result makes it clear that there is a tight correlation (0.992766) between the value of magnetic declination of any day and its predecessor 30-day data. The corrected determination coefficient 0.98506 means that our prognostic model, taking into account the predecessor 30 days, forecasts the probable value of the following day declination by nearly 99% on the eve.

Conclusion

The statistical study of the Dusheti Observatory (overall 19332 readings, y.y.1935-1950) shows that the dynamics of average annual values is characterized with 45-year cycle. Here statistically stable periodicity of increase of magnetic declination variations is distinguished. Namely, increase from minimal meaning to peak value needs approximately 15 years. There was a peak of such variation in 1952 and during the following 15 years a decrease took place. Further on, similar increase was observed during the next 15 years.

Taking into consideration, in our work we constructed an Adam deep learning network and received a high reliability prognostic model. The obtained model can be used for every-day forecasting as well as for more long-term prognoses.

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მაგნიტური (დუშეთი 1935-1989 წ.წ.) მიხრილობის სტატისტიკა და ღრმა თვითსწავლებადი მოდელი

თ. ქირია, ა. ესაკია, მ. ნიკოლაიშვილი, ე. ლომაძე

რეზიუმე

ნაშრომში წარმოდგენილია დუშეთის ობსერვატორიის მაგნიტური მიხრილობის საკმაოდ ხანგრძლივ (1935 – 1950 წ.წ., სულ 19332 ანათვალი) მონაცემთა ჯერ სტატისტიკური, ხოლო შემდეგ დღეისათვის ფართოდ გავრცელებული ე. წ. მანქანური სწავლების (ML) მეთოდის შესაძლებლობები. მოყვანილია ჰიპოთეზები ზოგიერთი გეომაგნეტური პარამეტრისთვის გარკვეული ფარული კანონზომიერებების და პერიოდულობის დასასაბუთებლად. დადგენილია მაღალი სტატისტიკური მდგრადობის მქონე ე. წ. „მეხსიერებები“. სწორედ ესაა ეტალონური ნიმუშები, რომელსაც ე. წ ადამის ღრმა სწავლების ქსელის გამოყენებით მიკუთვნების ფუნქციის ასაგებად ვიყენებთ.

Статистика магнитного склонения (Душети, 1935-1989 гг.) и модель глубокого самообучения

Т.В. Кириа, А.А. Эсакиа, М.М. Николайшвили, Э.Д. Ломадзе

Реферат

В статье представлены довольно длительные (1935 - 1950 г.г., всего 19332 отсчета) данные магнитного склонения обсерватории Душети, сначала статистические, а затем, широко используемые, методом машинного обучения (ML). Приводятся гипотезы для обоснования определенных скрытых закономерностей и периодичности некоторых геомагнитных параметров.

С высокой статистической стабильностью установлена т. н. "устоичивость". Это те стандартные образцы, которые мы используем с помощью сети глубокого самобучения Адама для построения функции принадлежности.