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Computer Simulation of Neural Networks Using Spreadsheets: Dr. Anderson, Welcome Back

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Abstract. The authors of the given article continue the series presented by the 2018 paper "Computer Simulation of Neural Networks Using Spreadsheets: The Dawn of the Age of Camelot". This time, they consider mathematical informatics as the basis of higher engineering education fundamentalization. Mathematical informatics deals with smart simulation, information security, long-term data storage and big data management, artificial intelligence systems, etc. The authors suggest studying basic principles of mathematical informatics by applying cloudoriented means of various levels including those traditionally considered supplementary - spreadsheets. The article considers ways of building neural network models in cloud-oriented spreadsheets, Google Sheets. The model is based on the problem of classifying multi-dimensional data provided in "The Use of Multiple Measurements in Taxonomic Problems" by R. A. Fisher. Edgar Anderson's role in collecting and preparing the data in the 1920s-1930s is discussed as well as some peculiarities of data selection. There are presented data on the method of multi-dimensional data presentation in the form of an ideograph developed by Anderson and considered one of the first efficient ways of data visualization.

Keywords: Anderson's Iris, cloud-based learning tools, computer simulation, mathematical informatics, neural networks, spreadsheets.

1 Introduction

The Fourth Industrial Revolution (Industry 4.0) actualized by the founder of the World Economic Forum, Klaus Schwab, has become a system-related challenge for the scientific community [15]. Industry 4.0 is primarily characterized by evolution and convergence of nano-, bio-, information and cognitive technologies to enhance high quality transformations in economic, social, cultural and humanitarian spheres. Professionals dealing with development and introduction of the sixth technological

paradigm technologies determine to a great extent whether our country is able to ride the wave of Industry 4.0 innovations. Therefore, extensive implementation of information and communication technologies (ICT) is a top priority of Ukraine's higher education updating in order to form a professionally competent specialist able to ensure the country's innovative development.

According to the Decree of the Cabinet of Ministers of Ukraine "Certain issues of specifying medium-term priorities of the national-level innovative activity for 2017-2021" (2016) [7], developing modern ICT and robotics, particularly cloud technologies, computer training systems and technologies of *mathematical informatics* (intellectual simulation, informational security, long-term data storage and "big data" management, artificial intelligence systems) are nationally and socially important directions of the innovative activity [10; 12].

The Decree of the Cabinet of Ministers of Ukraine "Certain issues of specifying medium-term priorities of the sectoral-level innovative activity for 2017-2021" (2017) [8] specifies that these directions accompanied by smart web-technologies and cloud computing make the basis for creating and defining themes for scientific researches and technical (experimental) developments as well as for forming the state order of training ICT specialists.

2 Literature Review and Problem Statement

Mathematical informatics is treated in two basic aspects:

1. as an area of

- theoretical research (mathematical models and means are used to simulate and investigate information processes in various areas of human activity);
- applied research (information systems and technologies are used to solve application-oriented problems).
- 2. as a subject which
- studies basic models, methods and algorithms of solving the problems in intellectualization of information systems;
- considers the issues of applying information models and information technologies of their study.

At the same time, the review in [9]] has revealed that in spite of the significant role of mathematical informatics in the computer sciences system, its models and methods are not applied to computer engineering and software engineering at Ukraine's higher educational institutions in a consistent manner.

In [11; 19; 23], the systematic training of students of technical universities (first of all, IT-students) in mathematical informatics is substantiated and its leading methods are determined. Introduction of mathematical informatics into university curricula is theoretically based on fundamentalization of professional training as a means of overcoming a gap between the training content and technological advance [24].

Future training in mathematical informatics results in IT specialists' ability to modify available and elaborate new information technologies based on models and methods of mathematical informatics in order to enhance the country's innovative development.

In [10] the role of neural network simulation in the training content of the special course "Foundations of Mathematical Informatics" is discussed. The course is developed for students of technical universities (future IT-specialists) and aimed at breaking a gap between theoretic computer science and its practical application to software, system and computing engineering. CoCalc is justified as a training tool for mathematical informatics in general and neural network modeling in particular. The elements of CoCalc techniques for studying the topic "Neural network and pattern recognition" within the special course "Foundations of Mathematical Informatics" are shown.

The authors of [16] distinguish basic approaches to solving the problem of network computer simulation training in the spreadsheet environment, joint application of spreadsheets and tools of neural network simulation, application of third-party add-ins to spreadsheets, development of macros using the embedded languages of spreadsheets; use of standard spreadsheet add-ins for non-linear optimization, creation of neural networks in the spreadsheet environment without add-ins and macros.

In [17; 18], there are opportunities for applying spreadsheets to introducing essentials of machine learning [13] at secondary and higher school as well as some elements of their application to solving problems of pattern classification.

Thus, using spreadsheets as a tool for teaching basics of machine learning creates conditions for early and simultaneously deeper mastering of corresponding models and methods of mathematical informatics [2].

3 The Aim and Objectives of the Study

Therefore, the *aim of the study* is to develop certain components of the methods of using electronic spreadsheets as a training tool for neural network simulation in the special course "Foundations of Mathematical Informatics".

To accomplish the set goal, the following tasks are to be solved:

- 1. substantiation of chosen sets of data to develop a model;
- development of a demonstration model of an artificial neural network using cloudoriented spreadsheets.

4 Edgar Anderson and His "Fisher's Iris Data Set" (1936)

Edgar Shannon Anderson (November 9, 1897 – June 18, 1969) was born in Forestville, New York (Fig. 1). According to George Ledyard Stebbins, from an early age he exhibited both superior intelligence and a great interest in plants, particularly in cultivating them and watching them grow [20, p. 4].



Fig. 1. Edgar Anderson's portrait and signature

He went to Michigan Agricultural College at the age of sixteen, just before his seventeenth birthday, knowing already that he wanted to be a botanist. After completing his degree, he accepted a graduate position at the Bussey Institution of Harvard University. After leaving Harvard with his doctor's degree in 1922, Anderson spent nine years at the Missouri Botanical Garden, where he was a geneticist and Director of the Henry Shaw School of Gardening; at the same time he was Assistant Professor, later Associate Professor, of Botany at Washington University in St. Louis. During this period, he developed the beginnings of his highly original and effective methods for looking at and recording variation in plant populations, as well as his keen interest in the needs and progress, both scientific and personal, of students in botany. His training in genetics had given him habits of precision and mathematical accuracy in observing and recording variation in natural populations that were entirely foreign to the taxonomists of that period [20, p. 5].

Through contacts with Jesse Greenman, Curator of the Garden Herbarium, he became aware of the enormous complexity and extent of the variation present in any large plant genus and of the need for understanding the origin of species as a major step in evolution. On extensive field trips he began to realize that a great amount of genetic variation exists within most natural populations of plants. This realization led him to the conclusion that "if we are to learn anything about the ultimate nature of species we must reduce the problem to the simplest terms and study a few easily recognized, well differentiated species" [4, p. 243].

He first selected *Iris versicolor*, the common blue flag, because he believed it to be clearly defined, and it was common and easily observed. Initially, this appeared to be a mistaken choice, since he soon found that Iris versicolor of the taxonomic manuals was actually two species, which, after preliminary analysis, he could easily tell apart. He then set himself the task of finding out, by a careful analysis of populations throughout

their geographic areas, how one of these species could have evolved from the other. He recorded several morphological characters in more than 2,000 individuals belonging to 100 populations, data far more extensive than those that any botanist had yet obtained on a single species.

In order to enable these data to be easily visualized and compared, he constructed the first of his highly original and extremely useful series of simplified diagrams or ideographs (Fig. 2). By examining them, he reached the conclusion that the variation within each of his two species was of another order from the differences between them; no population of one species could be imagined as the beginning of a course of evolution toward the other. He therefore concluded that speciation in this example was not a continuation of the variation that gave rise to differences between populations of one species, and started to look for other ways in which it could have taken place. The current literature offered a possible explanation: hybridization followed by chromosome doubling to produce a fertile, stable, true-breeding amphidiploid. To apply this concept to Iris, he had to find a third species that would provide an alternate parent for one of those studied. Going to the herbarium, he found it: an undescribed variety of *Iris setosa*, native to Alaska.

All of his data, including counts of chromosome numbers, agreed with the hypothesis that Iris versicolor of northeastern North America had arisen as an amphiploid, one parent being *Iris virginica* of the Mississippi Valley and the Southeast Coast and the other being Iris setosa var. interior of the Yukon Valley, Alaska. This was one of the earliest demonstrations that a plant species can evolve by hybridization accompanied or followed by chromosome doubling. Moreover, it was the first one to show that amphiploid or allopolyploid species could be used to support hypotheses about previous distribution of species.

Anderson's research into Iris resulted in all the techniques in his later successful work, namely:

- 1. careful examination of individual characteristics of plants growing in nature and progeny raised in the garden;
- reduction of this variation to easily visualized, simple terms by means of scatter diagrams and ideographs;
- 3. extrapolation from a putative parental species and supposed hybrids to reconstruct the alternative parent;
- 4. development of testable hypotheses by synthesizing data from every possible source.

The Iris research was Anderson's chief accomplishment during his first period at the Missouri Botanical Garden. Toward the end of this period, in 1929-1930, he received a National Research Fellowship to study in England. There he was guided chiefly by geneticist J. B. S. Haldane, but he also studied cytology under C. D. Darlington and statistics with R. A. Fisher. Haldane introduced him to the mutants of Primula sinensis, which he analyzed in collaboration with Dorothea De Winton. Their joint research was the first effort in plant material to relate pleiotropic gene action to growth processes.

In 1931 Anderson went to Harvard, where he stayed until 1935, as an arborist at the Arnold Arboretum. He returned to the Missouri Botanical Garden in 1935 and remained there for the rest of his life. Returning to his study of the genus Iris, he and several

students analyzed a complex variation pattern of populations found in the Mississippi delta region [3].

Anderson integrated his new experience with past memories, popular accounts of his methods of research, and his general philosophy of life in the book "Plants, Man and Life" [2] published in 1952. It is a combination of scientific knowledge, folklore of Latin American and other countries, and Anderson's comments on early herbalists and the habits of taxonomists and botany professors, plus a bit of philosophy. One of his chief contributions to plant science, the pictorialized scatter diagram, is presented for the first time in its final form in a chapter entitled, characteristically, "How to Measure an Avocado" (Fig. 2).

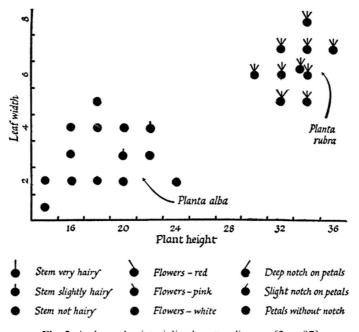


Fig. 2. Anderson's pictorialized scatter diagram [2, p. 97]

In 1954 Anderson became Director of the Missouri Botanical Garden, but he found fulltime administration frustrating and in 1957 resigned and resumed his career of teaching and research. During the 1960s he was plagued by illness, and his principal contributions during that period were a steady flow of popular articles on trees, shrubs, and other plants of the garden. He retired officially in 1967.

Anderson's article of 1936 [1] was his last work dedicated to the problem of Iris origin and classification. In his introduction to the article, Anderson not only expressed his gratitude to his English teachers, but also directly indicated that "Dr. Wright, Prof. J. B. S. Haldane, and Dr. R. A. Fisher have greatly furthered the final analysis of the data, though they are in no way responsible for the imperfections of the work or of its presentation." [1, p. 458].

In 1936, Sir Ronald Aylmer Fisher published the article "The Use of Multiple Measurements in Taxonomic Problems" indicating that "Table I shows measurements of the flowers of fifty plants each of the two species *Iris setosa* and *I. versicolor*, found growing together in the same colony and measured by Dr E. Anderson, to whom I am indebted for the use of the data" [6, p. 179-180]. Fisher's article contained only three references two of which to Anderson's works – that of 1935 [3] and that of [1] marked with "(in the Press)". In 1936, Fisher was not the member of the editorial board of "Annals of the Missouri Botanical Garden". The only way of his being aware of Anderson's article [1], was their personal correspondence.

The set of data used by Fisher and collected by Anderson was introduced as "Iris flower data set" (or "Iris data set" and "Iris data"). The phrase "Fisher's Iris data set" traditionally expresses Fisher's role as the founder of linear discriminant analysis, but not the authorship of the data set.

Although Anderson never published these data, he described [3] how he collected information on irises: "For some years I have been studying variation in irises but never before have I had the good fortune to meet such quantities of material for observation. On the simple assumption that if current theories are true, one should be able to find evidence of continuing evolution in any group of plants, I have been going around the world looking as sharply as possible at variation in irises. On any theory of evolution the differences between individuals get somehow built up, in time, into the differences between species. That is to say that by one process or another the differences which exist between one plant of *Iris versicolor* and its neighbor are compounded into the greater difference which distinguishes Iris versicolor from Iris setosa canadensis. It is a convenient theory and if it is true, we should be able to find the beginnings of such a compounding going on in our present day species. For that reason I have studied such irises as I could get to see, in as great detail as possible, measuring iris standard after iris standard and iris fall after iris fall, sitting squat-legged with record book and ruler in mountain meadows, in cypress swamps, on lake beaches, and in English parks. The result is still merely a ten year's harvest of dry statistics, only partially winnowed and just beginning to shape itself into generalizations which permit of summarization and the building of a few new theories to test by other means.

I have found no other opportunity quite like the field from De Verte to Trois Pistoles. There for mile after mile one could gather irises at will and assemble for comparison one hundred full-blown flowers of *Iris versicolor* and of *Iris setosa canadensis*, each from a different plant, but all from the same pasture, and picked on the same day and measured at the same time by the same person with the same apparatus. The result is, to ordinary eyes, a few pages of singularly dry statistics, but to the biomathematician a juicy morsel quite worth looking ten years to find.

After which rhapsody on the beauty of variation it must immediately be emphasized that *Iris setosa canadensis* varies but little in comparison with our other native blue flags. *Iris versicolor* in any New England pastures may produce ground colors all the way from mauve to blue and with hafts white or greenish or even sometimes quite a bright yellow at the juncture with the blade. *Iris setosa canadensis* by contrast is prevailingly uniform, its customary blue grey occasionally becoming a little lighter or a little darker or even a little more towards the purple, and its tiny petals producing odd

variants in form and pattern, but presenting on the whole only a fraction of the variability of *Iris versicolor* from the same pasture.

The reasons for this uniformity are not far to seek. Its lower chromosome number is one, but a discussion of that and its bearings on the whole problem would be a treatise in itself. More important probably is the fact that by geological and biological evidence, *Iris setosa canadensis* is most certainly a remnant, a relict *[sic]* of what was before the glacial period a species widely spread in northern North America.

If we take a map and plot thereon all known occurrences of *Iris setosa* and *Iris setosa* canadensis, we shall find the former growing over a large area at the northwest comer of the continent, and the latter clustering in a fairly restricted circle about the Gulf of St. Lawrence, while in the great intervening stretch of territory, none of these irises has been collected. This is a characteristic distribution for plants which were almost exterminated from eastern North America by the continental ice sheet, but while *[sic]* managed to persist in the unglaciated areas about the Gulf of St. Lawrence from which center they have later spread. In Alaska the species itself, *Iris setosa*, is apparently quite as variable as our other American irises."

So, we should pay tribute to Edgar Anderson by naming this data set after him – Anderson's Iris data set.

5 Model development

As indicated in [10], the special course "Foundations of Mathematical Informatics" final control of knowledge is a credit by the presentation of individual education and research projects on the artificial neural networks built by using CoCalc. Students can be offered to use cloud-based spreadsheets, Google Sheets, with the Solver additional cloud-based component (add-in) which is similar to "Solver" in Excel Online.

Let us consider the corresponding application method by taking a multi-dimensional data set (Anderson's Iris data set) to solve the pattern classification problem. Anderson's Iris is composed of data on 150 measurements of three Iris species (Fig. 3) – Iris setosa, Iris virginica and Iris versicolor) – including 50 measurements for each species.

There were measured four features (Fig. 4): sepal length (SL), sepal width (SW), petal length (PL), and petal width (PW).



Fig. 3. Anderson's Irises

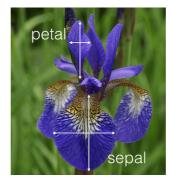


Fig. 4. Measurement features of Anderson's Irises

To draw a grounded conclusion on the Iris type, we build a three-layered neural network with the following architecture (Fig. 5):

- the input layer is a four-dimensional arithmetical vector (x_1, x_2, x_3, x_4) the components of which are corresponding measured features of Anderson's Irises (SL, SW, PL, PW) normalized according to the network activation function;
- the hidden layer has dimension 9 (the minimal required number according to Kolmogorov-Arnold representation theorem) and is described by the vector (h₁, h₂, h₃, h₄, h₅, h₆, h₇, h₈, h₉);
- the output layer is a three-dimensional arithmetical vector (y_1, y_2, y_3) the components of which are probabilities indicating the correspondence of the data set to one of the three Iris types.

The bias neuron equal to 1 (marked red in Fig. 5) is added to the neurons of the input and hidden layers. The bias neurons are noted for not having synapses so they cannot be located in the output layer.

Let us first introduce Anderson's Irises into spreadsheets with the following values of cells: A1 is Iris Data, A2 is SL, B2 is SW, C2 is PL, D2 is PW, E2 is Species.

The table cells A3:E152 include Anderson's Irises (Fig. 6).

We cannot input the data of the given set into the input layer as the value of the four characteristics is beyond the range limits [0; 1]. The next step is normalization of columns A, B, C and D to meet the given range and coding of Iris types from column E.

Each Iris type is coded by the three-dimensional arithmetical vector: for *i*-Iris (Iris setosa is 1, Iris versicolor is 2, Iris virginica is 3) we set the *i*-th component in 1, and the other ones – in 0. To do this, we introduce the following values into the cells: G1 is encoding, G2 is setosa, H2 is versicolor, I2 is virginica, G3 is =if(\$E3=G\$2,1,0).

Next, we copy the formula from the cell G3 to the range G3:I152 and obtain the following model codes for the three Iris types: for Iris setosa – (1, 0, 0), for Iris virginica – (0, 0, 1) and for Iris versicolor – (0, 1, 0).

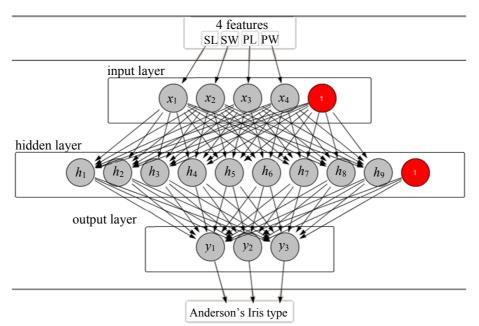


Fig. 5. Architecture of the neural network to solve the problem of Anderson's Iris classification

	А	в	С	D	E				
1	Iris Da	ata							
2	SL	SW	PL	PW	Species				
3	5.10	3.50	1.40	0.20	setosa				
4	4.90	3.00	1.40	0.20	setosa				
5	4.70	3.20	1.30	0.20	setosa				
6	4.60	3.10	1.50	0.20	setosa				
7	5.00	3.60	1.40	0.20	setosa				
8	5.40	3.90	1.70	0.40	setosa				

Fig. 6. The fragment of the spreadsheet of Anderson's Irises

Each column is normalized separately. To perform this, we find minimum and maximum values by introducing the following values: E154 is min, E155 is max, A154 is =min (A3:A152), A155 is =max (A3:A152).

We apply the cells A154:A155 to the range B154:D155 and introduce the following values into the cells: K1 is normalization, K2 is x_1 , L2 is x_2 , M2 is x_3 , N2 is x_4 , K3 is = (A3-A\$154) / (A\$155-A\$154).

The latter formula is a pplied to the range K3:N152. Its essence is explained by:

normalization =
$$\frac{\text{value} - \min}{\max - \min}$$
.

This approach results in the minimum value normalized to 0, while the maximum one - to 1.

According to the chosen architecture, we add the bias neuron to the four neurons of the input layer by introducing its name (x_5) into the cell O2 and its value (1) into the range O3:O152. On this stage, the input layer is formed as x_1 , x_2 , x_3 , x_4 , x_5 .

The next step includes transmission of a signal from the input layer to the hidden one of the neural network. We denote the weight coefficient of the synapse connecting the neuron x_i (i = 1, 2, 3, 4, 5) of the input layer with the neuron h_i (j = 1, 2, ..., 9) of the hidden layer by w^{xh}_{ij} , while the weight coefficient connecting the neuron h_i of the hidden layer with the neuron y_k (k = 1, 2, 3) of the input layer is denoted by w^{hy}_{ik} . In this case, the force of the signal coming to the neuron h_i of the hidden layer is determined as a scalar product of signal values on the input signals and corresponding weight coefficients. To determine a signal going further to the output layer, we apply the logistic function of activation $f(S) = 1/(1+e^{-S})$, where S is a scalar product. The formulae for determining the signals on the hidden and output layers will look like:

$$h_j = f\left(\sum_{i=1}^{4+1} x_i w_{ij}^{xh}\right), y_k = f\left(\sum_{j=1}^{9+1} x_i w_{jk}^{hy}\right).$$

Accordingly, two matrices should be created. The matrix w^{xh} of 5×9 contains weight coefficients connecting five neurons of the input layer (the first four contain normalized characteristics of Anderson's Irises, while the fifth one is the bias neuron) with the neurons of the hidden layer. The matrix w^{hy} of 10×3 contains weight coefficients connecting ten neurons of the hidden layer (nine of which are calculated and the tenth one is the bias neuron) with the neurons of the bias neuron) with the neurons of the output layer. For the "untaught" neural network, initial values of the weight coefficients can be set either randomly or left undetermined or equal to zero. To realize the latter, we fill the cells with the following values: R1 is w^{xh} , Q2 is input/hidden, R2 is 1, S2 is =R2+1, Q3 is 1, Q4 is =Q3+1, R3 is 0, R9 is w^{hy} , Q10 is hidden/output, R10 is 1, S10 is =R10+1, Q11 is 1, Q12 is =Q11+1, R11 is 0.

To create the matrices, we should copy the cells R3 into the range R3:Z7, R11 – into R11:T20, S2 – into T2:Z2, Q4 – into Q5:Q7, S10 – into T10, Q12 – into Q13:Q20 (Fig. 7).

To calculate the scalar product of the vector row of the input layer values by the matrix vector-column of the weight coefficients w^{hy} , we should apply the matrix multiplication function: AB1 is calculate the hidden layer, AB2 is h_1 , AC2 is h_2 , AD2 is h_3 , AE2 is h_4 , AF2 is h_5 , AG2 is h_6 , AH2 is h_7 , AI2 is h_8 , AJ2 is h_9 , AK2 is h_{10} , AB3 is =1/(1+exp(-mmult(\$K3:\$03, R\$3:R\$7))), AK3 is 1.

Next, we copy the cell AK3 into the range AK4:AK152, while AB3 – into AB3:AJ152.

Considering the fact that all the matrix elements of the weight coefficients w^{xh} equal to zero, after duplicating the formulae, the calculated elements of the hidden layer will be equal to 0.5.

In the same way, we calculate the output layer elements: AM1 is calculate the output layer, AM2 is y_1 , AN2 is y_2 , AO2 is y_3 , AM3 is =1/(1+exp(-mmult(\$AB3:\$AK3,R\$11:R\$20))).

_	G	н	1.1	J	к	L	м	N	0	Р	Q	R	S	т	U	V	W	x	Y	Z
1	encodir	encoding			normali	zation						wxh								
2	setosa	versicolor	virginica		x1	x 2	x 3	x4	x5		input/hidden	1	2	3	4	5	6	7	8	9
3	1	0	0		0.2222	0.6250	0.0678	0.0417	1		1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0
4	1	0	0		0.1667	0.4167	0.0678	0.0417	1		2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0
5	1	0	0		0.1111	0.5000	0.0508	0.0417	1		3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0
6	1	0	0		0.0833	0.4583	0.0847	0.0417	1		4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0
7	1	0	0		0.1944	0.6667	0.0678	0.0417	1		5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0
8	1	0	0		0.3056	0.7917	0.1186	0.1250	1											
9	1	0	0		0.0833	0.5833	0.0678	0.0833	1			why								
10	1	0	0		0.1944	0.5833	0.0847	0.0417	1		hidden/output	1	2	3						
11	1	0	0		0.0278	0.3750	0.0678	0.0417	1		1	0.00	0.00	0.00						
12	1	0	0		0.1667	0.4583	0.0847	0.0000	1		2	0.00	0.00	0.00						
13	1	0	0		0.3056	0.7083	0.0847	0.0417	1		3	0.00	0.00	0.00						
14	1	0	0		0.1389	0.5833	0.1017	0.0417	1		4	0.00	0.00	0.00						
15	1	0	0		0.1389	0.4167	0.0678	0.0000	1		5	0.00	0.00	0.00						
16	1	0	0		0.0000	0.4167	0.0169	0.0000	1		6	0.00	0.00	0.00						
17	1	0	0		0.4167	0.8333	0.0339	0.0417	1		7	0.00	0.00	0.00						
18	1	0	0		0.3889	1.0000	0.0847	0.1250	1		8	0.00	0.00	0.00						
9	1	0	0		0.3056	0.7917	0.0508	0.1250	1		9	0.00	0.00	0.00						
20	1	0	0		0.2222	0.6250	0.0678	0.0833	1		10	0.00	0.00	0.00						

Fig. 7. The fragment of the spreadsheet after coding and normalization of the output data and creation of the matrices of the weight coefficients

Next, we copy the cell AM3 to the range AM3:AO152 (Fig. 8).

fx =1/(1+exp(-mmult(\$AB3:\$AK3,S\$11:S\$20)))

	AB	AC	AD	AE	AF	AG	AH	AI	AJ	AK	AL	AM	AN	AO
1	calculat	e the hid	lden laye	r								calculate	the outpu	ıt layer
2	h1	h2	h3	h4	h5	h6	h7	h8	h9	h10		y1	y2	y3
3	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	1		0.5000	0.5000	0.5000
4	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	1		0.5000	0.5000	0.5000

Fig. 8. The fragment of the spreadsheet of calculating the hidden and output layers with initial values of the weight coefficients

Neural network training is performed by varying weight coefficients so that with each training step the difference between the calculated values of the output layer and the desired (reference ones) reduces. To solve the problem, the three-dimensional vectors resulted from coding of the three Iris types are reference.

To find the difference between the calculated and the reference output vectors we apply the Euclidean distance: AQ2 is distance, AR2 is sum of distances, AQ3 is =sqrt((AM3-G3)^2+(AN3-H3)^2+(AO3-I3)^2), AR3 is =sum(AQ3:AQ152).

Next, we copy the cell AQ3 to the range AQ4:AQ152. The cell AR3 contains general deviation of the calculated output vectors from the reference ones.

Under this approach, the neural network training can be treated as an optimization problem in which the target function (the sum of distances in the cell AR3) will be minimized by varying the matrix weight coefficients w^{xh} (the range R3:Z7) and w^{hy} (the range R11:T20). To solve this problem, application of cloud-oriented spreadsheets (Google Sheets) is not enough and it is necessary to install an additional cloud-oriented component (add-in) Solver.

Adjustment of the add-in Solver to solve the set goal: the target function (Set Objective) is minimized (To: Min) by changing the values (By Changing) of the matrix

weight coefficients in the range (Subject To) from -10 to +10 by one of the optimization methods (Solving Method).

To reduce the total distances, the actions with Solver can be done repeatedly as it is expedient to experiment with combination of various optimization methods by changing the variation limits of the weight coefficients. It is not necessary to try to reduce the value of the total distances to zero as this can be a greater (quite smaller) value (Fig. 9).

fx	=sum(/	AQ3:AQ1	52)												Set Objective			
	AF	AG	AH	AI	AJ	AK	AL	AM	AN	AO	AP	AQ	AR		AR3			
1								calculate	the outpu	it layer				-				
2	h5	h6	h7	h8	h9	h10		y1	y2	y3		distance	sum of distances	•		Min Value	e Of:	
3	0.9993	1.0000	0.9926	0.9994	1.0000	1		1.0000	0.0000	0.0000		0.0000	1.4329		By Changing			
4	0.9977	0.9999	0.9908	0.9976	0.9998	1		1.0000	0.0001	0.0000		0.0001			R3:Z7,R11:T	20		
5	0.9993	1.0000	0.9913	0.9994	0.9997	1		1.0000	0.0000	0.0000		0.0000			Subject To:			
6	0.9990	0.9999	0.9911	0.9990	0.9988	1		1.0000	0.0000	0.0000		0.0000			R3:Z7 <= 20 R3:77 >= -2			
7	0.9996	1.0000	0.9928	0.9997	0.9999	1		1.0000	0.0000	0.0000		0.0000			R11:T20 <= 20 R11:T20 >= -20			
8	0.9986	1.0000	0.9691	0.9990	1.0000	1		1.0000	0.0000	0.0000		0.0000						
9	0.9995	1.0000	0.9818	0.9996	0.9988	1		1.0000	0.0000	0.0000		0.0000						
10	0.9991	1.0000	0.9923	0.9992	0.9999	1		1.0000	0.0000	0.0000		0.0000						
11	0.9990	0.9999	0.9901	0.9989	0.9973	1		1.0000	0.0000	0.0000		0.0000						
12	0.9986	0.9999	0.9962	0.9987	0.9998	1		1.0000	0.0000	0.0000		0.0000						
13	0.9991	1.0000	0.9933	0.9993	1.0000	1		1.0000	0.0000	0.0000		0.0000						
14	0.9993	1.0000	0.9923	0.9994	0.9995	1		1.0000	0.0000	0.0000		0.0000			Add Change		Delete	
15	0.9987	0.9999	0.9960	0.9987	0.9998	1		1.0000	0.0000	0.0000		0.0000						
6	0.9998	0.9999	0.9957	0.9997	0.9988	1		1.0000	0.0000	0.0000		0.0000			Solving Meth	od:		
7	0.9995	1.0000	0.9940	0.9996	1.0000	1		1.0000	0.0000	0.0000		0.0000			Standard Int	erval Global		

Fig. 9. Optimization results

On the assumption of the chosen coding method, the output vector actually contains three probabilities: y_i denotes the probability of the given sample being the *i*-type Iris, where i = 1 for Iris setosa, 2 for Iris versicolor and 3 for Iris virginica. Then, to find out which Iris type describes the input vector (SL, SW, PL, PW), the most probable component should be determined.

To do this, we fill the cells in the following way: AT2 is Calculated Iris species, AT3 is =if(max(AM3:AO3)=AM3,\$G\$2,if(max(AM3:AO3)=AN3,\$H\$2, \$I\$2)), AU3 is =if(AT3=E3,"right!","wrong").

Next, the range AT3:AU3 is copied to the range AT4:AU152.

The obtained result enables us to visualize pattern recognition simulated in spreadsheets. The built model will be considered relevant in all 150 cases, the column AU contains the value "right!".

To check the limits of the built model application, we try to input the vector not coinciding with any reference input vector. For this, we copy the table row 152 to 158 and delete the content of the cells E158:I158, AQ158, AU158. We introduce averaged values borrowed from the description of Iris versicolor in the article by Anderson [11, p. 463]: 5.50, 2.75, 3.50 and 1.25. The reference values $x_1 = 0.3333$, $x_2 = 0.3125$, $x_3 = 0.4237$, $x_1 = 0.4792$ are conveyed to the input layer, while on the hidden layer there are calculated $h_1 = 0.0206$, $h_2 = 0.4419$, $h_3 = 0.0005$, $h_4 = 0.0001$, $h_5 = 0.9993$, $h_6 = 0.9993$, $h_7 = 0.0001$, $h_8 = 0.0288$, $h_9 = 0.9991$ and the values of the output layer $y_1 = 0.0000$, $y_2 = 1.0000$, $y_3 = 0.0000$. As the maximum value of the output layer 1.0000 corresponds to the other Iris type, we can conclude that Iris versicolor is identified.

6 Conclusions

- 1. Edgar Anderson appeared to be not a simple botanist whose data were the basis for Fisher's known method. Anderson's Irises resulted from his long experience of working out relevant models to describe changes in specific populations by means of a limited number of characteristics. Yet, Anderson had also coped with the opposite problem of building simple multi-dimensional data interpretation 40 years before Chernoff faces appeared [5].
- 2. The described methods of applying cloud-oriented spreadsheets as a tools for training mathematical informatics can enable solution of all basic problems of neural network simulation. The only limitation is not so much the volume of a spreadsheet as the memory space and the speed of the device processing it. In the special course projects if the limitation is overcome, this becomes a stimulus for replacing the simulation environment by a more relevant one [22].
- 3. The further research is the Dawn of the Age of Camelot: from Donald Hebb to Seymour Papert [17].

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