WHOSE TOOLS ARE THESE? AN ARTIFICIAL NEURAL NETWORK APPLIED TO THE CLASSIFICATION OF OLD KINGDOM EGYPTIAN CHISELS*

https://doi.org/10.31577/aassav.2023.32.2.02

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This paper presents an attempt to apply advanced computational methods to a database of Old Kingdom Egyptian copper model tools. We examine a particular class of artefacts, chisels. A smaller dataset extracted from them was used to train several linear and non-linear classification models. All these models were able to *classify* the items according to their origin, the site or part of site where they were found. The origin of the chisels was set against a working hypothesis in an attempt to establish the provenance of some chisels, presumably ones coming from excavations by Hermann Junker at Giza, currently in the collection of the Kunsthistorisches Museum in Vienna. The classification model has corroborated the indications of other contextual information, and the tentative provenance of the assemblages in the Western Field at Giza is proposed. Another set of predictions was influenced by fragments of chisels, particularly those described in the database from Abusir South, which skewed the predictions of other fragmentary pieces towards this site.

Keywords: Machine learning, Old Kingdom Egypt, chisel, classification model

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* In the case of Martin Odler, the work was supported by the European Regional Development Fund Project "Creativity and Adaptability as Conditions of the Success of Europe in an Interrelated World" (No. CZ.02.1.01/0.0/16_019/0000734).

Introduction

Ancient Egypt intrigues specialists and the general public alike with hundreds of sites and thousands of artefacts excavated especially during the last two centuries. However, Egyptian archaeology paid much more attention to inscribed material culture in the past while objects without inscriptions were deemed less important. Although the situation is getting better, data description and data analysis have seldom moved beyond catalogue descriptions and catalogue evaluations with traditional typological and morphological analyses in the mind and in practical use. Since our article deals with copper alloy objects, we list examples of such publications dealing with copper alloy artefacts.[1] Catalogue presentations of the data are accompanied by illustrations of the material along with Egyptological and, less often, archaeological evaluation. Though these are certainly highly valuable works in themselves, current analytical possibilities go further.

This paper presents an attempt to apply advanced computational methods to a database of Old Kingdom copper model tools. The tools were studied before, and a catalogue with an evaluation was published.[2] In this article we seek to examine the database of one specific category, chisels, in more detail in order to find out whether computational methods can add a significant new level of information to the studied assemblage. Specifically, we aim to demonstrate that a detailed database description of the artefacts can help traditional typological and morphological analysis determine the most probable origin of objects with unknown or merely hypothetical provenance. This approach could help in the identification of the most probable provenance of unprovenanced objects based on a numerical and structural description of the artefacts. A clear advantage in comparison with traditional typology is that the process is controlled. The method presented herein is quite simple and easily applicable to data evaluation, provided that the model is accommodated to existing data.

Advanced mathematical and computational tools can be used to analyse data and create models automatically. The aim of the present work is to create a *classification* model. Rather than a quantitative (or numerical) result, a classification model provides a qualitative one, dividing the inputs into *classes. For instance: is this picture a car? or is it a flower?* In our case, the classes are

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[1] DAVIES, W. V. *Catalogue of Egyptian Antiquities in the British Museum. 7: Tools and Weapons; 1: Axes*; KÜHNERT-EGGEBRECHT, E. *Die Axt als Waffe und Werkzeug im alten Ägypten*; LILYQUIST, C. *Ancient Egyptian Mirrors: from the Earliest Times through the Middle Kingdom*.

[2] ODLER, M. *Old Kingdom Copper Tools and Model Tools. With Contributions by Jiří Kmošek, Ján Dupej, Katarína Arias Kytnarová, Lucie Jirásková, Veronika Dulíková, Tereza Jamborová, Šárka Msallamová, Kateřina Šálková and Martina Kmoníčková*.

the different archaeological sites from which individual metal implements originate. We follow up the topics of some previous archaeological studies (see below).

Beyond classical statistics, which is used to *describe* data, there are techniques like *machine learning* which allow us not only to analyse the structure of the data but also to make predictions from it. The benefits of such techniques extend into many fields. In particular, supervised learning tools, like *regression* and *classification*, are used to produce predictive models, while unsupervised learning tools like *clustering analysis* are used to extract information on the underlying structure in the data. *Supervised learning* is characterised by a model training process in which a set of samples, paired to a set of *answers*, or *labels*, is provided. The model thus constructed should be able to correctly describe the phenomenon and therefore to predict the correct *answers*, or *labels*, for new samples. All these tools assist many modern industries and research disciplines in taming many a complex phenomenon.[3]

Data analysis tools such as automated classification make an invaluable contribution to disciplines like archaeology that may be grouped into two categories. Firstly, they make it possible to classify archaeological items almost effortlessly compared to the effort required when doing it by human experts, liberating the capabilities of those experts for analysis rather than description. On the other hand, the same characteristics of an automated method force us to reflect on the consistency of the rules used in the classification process. Indeed, a machine will use a set of rules systematically and without exceptions; therefore, the rules it applies need to cover all conceivable possibilities and be consistent in themselves.

The growing relationship between archaeology and computer science and related technologies dates back to the late 1960s. As Whallon describes, from the 1960s to the early 1970s the amount of archaeological work that found a use for the rapidly developing computer applications increased dramatically.[4] In

[3] BHADESHIA, H. K D. H. Neural Networks in Materials Science. In *ISIJ International*, 1999, Vol. 39, No. 10 [online]. DOI: https://doi.org/10.2355/isijinternational.39.966; EATON, J. W. et al. GNU Octave version 4.0.0 manual: a high-level interactive language for numerical computations [online] [cit. 29 July 2019]; GAUDE-FUGAROLAS, D. *Modelling of Transformations during Induction Hardening and Tempering* [online] [cit. 29 July 2019]. DOI: https://doi.org/10.17863/CAM.14223; MACKAY, D. J. C. *Information Theory, Inference and Learning Algorithms*; NG, A. Machine Learning. In *Coursera Online Course* [online] [cit. 29 July 2019]. Available from https://www.coursera.org/learn/machine-learning.

[4] WHALLON, R. The Computer in Archaeology: A Critical Survey. In *Computers and the Humanities*, 1972, Vol. 7, No. 1.

particular, the need to deal with large amounts of data, so common in archaeology, is especially suited to being assisted by information technology. Furthermore, the very limitations of information technology, like its inability to deal with unexpected exceptions and the draconian need of strict definitions, in turn contribute to archaeology by emphasising the need to follow very precise definitions and systematic classification schemes.[5]

The technologies used at that time were more often related to description, seriation, clustering, structured data storage, etc.[6] Moreover, the use of archiving and database implementation and management, computer-assisted classification is one of the techniques often mentioned in archaeological work.[7] Computer technology has been used in clustering and classification studies either as an aid, for semi-automated classification or all the way to automatic classification or clustering using machine learning techniques.[8]

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5 WHALLON, R. The Computer in Archaeology: A Critical Survey. In *Computers and the Humanities*, 1972, Vol. 7, No. 1.

6 Ibid.

7 KARASIK, A., SMILANSKY, U. Computerized Morphological Classification of Ceramics. In *Journal of Archaeological Science*, 2011, Vol. 38, No. 10 [online]. DOI: https://doi.org/10.1016/j.jas.2011.05.023; NGUIFO, E. M. et al. PLATA: An Application of LEGAL, a Machine Learning Based System, to a Typology of Archaeological Ceramics. In *Computers and the Humanities*, 1997, Vol. 31, No. 3; SMITH, N. G. et al. The "Pottery Informatics Query Database": A New Method for Mathematic and Quantitative Analyses of Large Regional Ceramic Datasets. In *Journal of Archaeological Method and Theory*, 2014, Vol. 21, No. 1.

8 HÖRR, C., LINDINGER, E., BRUNNETT, G. Machine Learning Based Typology Development in Archaeology. In *J. Comput. Cult. Herit*, 2014, Vol. 7, No. 1 [online]. DOI: https://dl.acm.org/doi/10.1145/2533988; KARASIK, A., SMILANSKY, U. Computerized Morphological Classification of Ceramics [online]. DOI: https://doi.org/10.1016/j.jas.2011.05.023; MARTINO, S., MARTINO, M. A Quantitative Method for the Creation of Typologies for Qualitatively Described Objects. In *CyberResearch on the Ancient Near East and Neighboring Regions: Case Studies on Archaeological Data, Objects, Texts, and Digital Archiving* [online]. Available from http://www.jstor.org/stable/10.1163/j.ctv4v349g.13; NGUIFO E. M. et al. *PLATA: An Application of LEGAL, a Machine Learning Based System, to a Typology of Archaeological Ceramics*; SMITH, N. G. et al. The "Pottery Informatics Query Database": A New Method for Mathematic and Quantitative Analyses of Large Regional Ceramic Datasets. In *Journal of Archaeological Method and Theory*, 2014, Vol. 21, No. 1.

1. Description and Context of the Data

As has already been mentioned, the data we use have been published previously.[9] They cover copper tools and model tools from the Old Kingdom of ancient Egyptian history, defined for these objects as a period from Dynasty 4 to Dynasty 6 (c. 2600 – 2180 BC),[10] the era that saw the building of the largest pyramids. Full-size, practically used functional tools were scarce and most probably recycled; the most frequent assemblages found in the burial equipment of the Old Kingdom elite were sets of model tools with copper blades and sometimes wooden handles. It was argued in the monograph, cited in Footnote 9, that these are symbols of the patron – craftsman dependence, of the ability of the elites to order and support the craftwork of artisans. Craftwork was one of the aspects of the life of the elites; its members were often depicted on reliefs or paintings in Old Kingdom tombs watching craft activities in so-called *mꜣꜣ*-scenes. It was assumed that as these activities were indispensable for life, they would be needed also in the Afterlife to support the Netherworld existence of the member of social elite.

Tools were most frequently found in cemeteries near the capital of the Old Kingdom state, Memphis. Of the 429 Old Kingdom contexts in the database, 133 were from Giza, comprising more than one-fourth of the data;[11] together with data from Abusir (51 contexts) and Saqqara (32 contexts), the count reaches 216 contexts, almost half of the corpus coming from the cemeteries of the Old Kingdom capital. The data are thus heavily skewed towards the central cemeteries of the state. Another factor is that the corresponding author of this article worked with Old Kingdom material at Abusir South, which means that current data from these excavations are better accessible (see below for the evidence that this factor has indeed influenced the model). Besides being the main foci of archaeological research, this situation most probably reflects also the past reality of the most frequent burial activity in the Old Kingdom.

The model tool assemblages comprised most frequently four artisan tool categories: chisels, adzes, axes, and saws. Of these, the category of chisels (**Fig. 1**), ancient Egyptian artisan tools *par excellence*, is the most numerous and best preserved by far.[12] The database in the monograph included 918 chisels, which were divided into three main shape categories based on traditional

[9] ODLER, M. *Old Kingdom Copper Tools and Model Tools.*
[10] For the chronology, see BRONK RAMSEY, C., SHORTLAND, A. J. *Radiocarbon and the Chronologies of Ancient Egypt*; HORNUNG, E., KRAUSS, R., WARBURTON, D. *Ancient Egyptian Chronology*.
[11] ODLER, M. *Old Kingdom Copper Tools and Model Tools*, p. 65.
[12] Ibid., pp. 103–128.

typological and morphological study (**Fig. 2**): flat chisels (Types A–C); cross-cut chisels, with the widest edge of the blade turned 90° from the widest edge of the chisel shaft (Types D–F) and pointed picks (Type G). The descriptors include fundamental metric and structural properties of all chisels, thus describing them in sufficient detail. The database has been revised for the purpose of the present study: the descriptions were completed and newly documented material from studies since 2016 added, creating the assemblage of 947 chisels used in this study.

The assemblage includes also chisels whose place of origin is hypothetical or unknown. Most of this "unknown" assemblage is currently stored in the Kunsthistorisches Museum in Vienna; it is assumed that the objects might come from the excavations at Giza by Hermann Junker (**Fig. 3**). The results of the excavation were published in twelve volumes.[13] The bulk of the material was identified in the museum collections of Austrian and German museums (**Table 1**). However, the exact tomb numbers were not established in the case of some contexts and as such, they were published recently (Contexts G123 to G129 with chisels, in [14]). A practical aim of this paper is to demonstrate the ability of advanced statistical methods in helping to assess the most probable provenance of the artefacts based on a comparison with already described specimens. This would make it possible to assess the origin of unknown artefacts with the help of a simple and easily-structured variable description.

[13] JUNKER, H. *Gîza I: Die Maṣṭabas der beginnenden V. Dynastie auf dem Westfriedhof*; JUNKER, H. *Gîza II: Die Maṣṭabas der beginnenden V. Dynastie auf dem Westfriedhof*; JUNKER, H. *Gîza III: Die Maṣṭabas der vorgeschrittenen V. Dynastie auf dem Westfriedhof*; JUNKER, H. *Gîza IV: Die Maṣṭaba des kAjmanx (Kai-em-anch)*; JUNKER, H. *Gîza V: Die Maṣṭabas des Cnb (Seneb) und die umliegenden Gräber.*; JUNKER, H. *Gîza VI: Die Maṣṭaba des nfr (Nefer), qdfjj (Kedfi), kAhjf (Kahjef) und die westlich anschließenden Grabanlagen*; JUNKER, H. *Gîza VII: Der Ostabschnitt des Westfriedhofp. Erster Teil*; JUNKER, H. *Gîza VIII: Der Ostabschnitt des Westfriedhofs, Zweiter Teil*; JUNKER, H. *Gîza IX: Das Mittelfeld des Westfriedhofp*; JUNKER, H. *Gîza X: Der Friedhof südlich der Cheopspyramide, Westteil.*; JUNKER, H. *Gîza XI: Der Friedhof südlich der Cheopspyramide, Ostteil.*; JUNKER, H. *Gîza XII: Schlussband mit Zusammenfassungen und Gesamt-Verzeichnissen von Band I–XII.*

[14] ODLER, M. *Old Kingdom Copper Tools and Model Tools*, p. 75, Fig. 47.

2. Dataset, Variable Selection, and Data Treatment

2.1 Database

Data analysis techniques such as classification usually benefit from using a large set of data. A recently updated dataset on Old Kingdom metal tools compiled by Martin Odler was used as a source to develop a mathematical classification model for archaeological data. Of the several databases compiled, the chisel database (containing 947 samples from various sites) is one of the larger ones.

At the same time, the target parameter needs to be described by a sufficient number of relevant parameters. Regarding that, an important requirement is that the information on the database should be consistent, that is, that information on all the relevant parameters be available for each sample, without any gaps. In this work, the model attempts to classify items according to their sites of origin. Suitable parameters describing the features of each item are either descriptive or related to the dimensions of the item, i.e. the artefact.

The descriptive parameters include features such as the shape of the cross-section, the presence of bevelling, *etc*., while the metric ones are related to the size of the item (the length and an estimate of the volume). The target parameter, or *label*, is the site (or part of site) of origin of the item.

For both types of features there are gaps in the datasets. Machine-learning modelling tools are not usually capable of dealing with missing data. However, there are ways to overcome this problem, as described below.

2.2 Feature Selection

The target variable is the origin of each of the items. Because the individual sites have provided different numbers of samples for study, a combination of excavation Site and Part of Site was used in an effort to obtain a more balanced distribution. Excavation sites providing numerous samples were divided into smaller Part of Site groups, while some sites providing fewer samples were grouped together. The reasons are explained below, the main one being the need to split the assemblage into meaningful spatial and chronological units.

In order to analyse the data with the aim of creating a classification model, enough samples of each origin are needed. Sites providing only a few samples were discarded. That left 892 samples. Of those, 66 do not have complete information as to their origin. Removing these during the training of the model left a dataset with 826 samples for which we have information about their provenance and that can be described by variables.

It is of no less importance that each of the samples used needs to have information on all the features used to describe the item. As this was not the case for many of the samples in the dataset, measures were taken to reduce the effect of that problem.

2.3 Description of Features

The following features were used as descriptors of each item in this work: Category; Type; Handle; Burr; Thread; Shoulder; Side; Section of Shaft; Bulges; Bevelling; Flaring of Edge; Edge Shape; Length of Chisel; Rod Volume. These descriptors involving the main morphological features of the chisels are discussed in detail elsewhere.[15] These features are metrical (Length of Chisel; Rod Volume – calculated as a multiplication of the length of the chisel by its diameter or width, thus providing a rough estimate of the volume of the copper alloy bar needed for the production of the chisel), morphological, with a verbal description of the separate states and shapes of the chisels (Handle; Burr; Thread; Shoulder; Side; Section of Shaft; Bulges; Bevelling; Flaring of Edge; Edge Shape) and broader categories of either full-size functional objects or models and types, as defined by the traditional archaeological sorting of chisels. The terminology is largely based on definitions previously used for Bronze Age Minoan chisels.[16]

2.4 Description of Labels: Site/Part of Site

The main problem for most of the sites was the small number of specimens found and sufficient for the description (**Fig. 4; Table 2**). This was the case of the sites of Abu Rawash,[17] Abydos,[18] Balat[19] and Saqqara,[20] where the number of chisels

[15] ODLER, M. *Old Kingdom Copper Tools and Model Tools*, pp. 99–128, Figs. 90–93.
[16] EVELY, D. *Minoan Crafts: Tools and Techniques; An Introduction.* Vol. 1, Fig. 2.
[17] BISSON DE LA ROQUE, F. *Rapport sur les fouilles d'Abou-Roasch (1922 – 1923)*; BISSON DE LA ROQUE, F. *Rapport sur les fouilles d'Abou-Roasch (1924)*.
[18] GARSTANG, J. Excavations at Abydos, Preliminary Description of the Principal Finds. In *Annals of Archeology and Anthropology 2*, 1909, Vol. 2.
[19] CHERPION, N., CASTEL, G., PANTALACCI, L. *Balat V: Le mastaba de Khentika: tombeau d'un gouverneur de l'oasis à la fin de l'ancien empire*; SOUKIASSIAN, G., WUTTMANN, M., PANTALACCI, L. *Balat VI: Le palais des gouverneurs de l'époque de Pépy II: les sanctuaires de ka et leurs dépendances*; VALLOGGIA, M. *Balat I: Le Mastaba de Medou-Nefer*, 1986.
[20] BRUNTON, G. The Burial of Prince Ptah-Shepses at Saqqara. In *Annales du Service des Antiquités de l'Égypte*, 1947, Vol. 47; FIRTH, C. M., GUNN, B. *Teti Pyramid*

was nevertheless sufficient to be included in the model. The material from the site of Abusir was gradually being studied by the second author of the article as new assemblages came to light, and their description is most detailed. The number of the assemblages from Giza was also high, but they are distributed throughout the site and its chronology (**Fig. 5; Table 3**); therefore, we have grouped tombs of Cemetery G I S[21] and the settlement south of the causeway of Menkaure[22] as the first and oldest group from early Dynasty 4, with the Eastern Field (Dynasty 4) and the Western, Central and Southern Fields (predominantly late Dynasty 4 to Dynasty 6) as separate site parts, as the chronological and morphological differences between them are significant.

The sites (or parts of site) used as labels when building the model were the following:

- (1) Abu Rawash
- (2) Abusir South
- (3) Abusir Centre (including Djedkare Family Cemetery;[23] Royal Cemetery with the minor tombs[24])
- (4) Abydos
- (5) Balat
- (6) Giza: Eastern Field
- (7) Giza: Western Field
- (8) Giza: Central Field
- (9) Giza: Southern Field
- (10) Giza: Menk-CIS, including the settlement south of the causeway of the pyramid of Menkaure, the pyramid complex of Menkaure and Cemetery G I S
- (11) Saqqara

Cemeteries I–II; JAMES, T. G. H. *The Mastaba of Khentika Called Ikhekhi*; KANAWATI, N. *The Teti Cemetery at Saqqara VIII. The Tomb of Inumin*; KOWALSKA, A. Finds: Small Finds. In MYŚLIWIEC, K. (ed.). *Saqqara: Polish-Egyptian Archaeological Mission. V Old Kingdom Structures between the Step Pyramid Complex and the Dry Moat. Pt. 2: Geology, Anthropology, Finds, Conservation*.

[21] REISNER, G. A., SMITH, W. P. *A History of the Giza Necropolis, Volume 2: The Tomb of Hetep-Heres, the Mother of Cheops: A Study of Egyptian Civilization in the Old Kingdom*.

[22] KROMER, K. *Siedlungsfunde aus dem frühen Alten Reich in Giseh: österreichische Ausgrabungen 1971 – 1975*.

[23] VERNER, M., CALLENDER, V. G. *Djedkare's Family Cemetery*.

[24] KREJČÍ, J., CALLENDER, V. G., VERNER, M. (eds.). *Minor Tombs in the Royal Necropolis I: the Mastabas of Nebtyemneferes and Nakhtsare, Pyramid Complex Lepsius No. 24 and Tomb Complex Lepsius No. 25*.

2.5 Data Treatment and Dealing with Missing Data

As mentioned above, to be able to use a dataset to train a classification model, each of the samples used needs to have information on all the features used to describe it. This was not the case for many of the samples in the dataset used, but measures were taken to reduce the effects of that problem. In the case of descriptive features (*i.e.* the shape of the section), each of the characteristics (and options within each feature) has been considered as a binary feature (*i.e.* either having a square section or not); this expanded the number of features considered but made it possible to compensate for the lack of information on some of those features.

Dealing with missing data becomes a little more complex for quantitative features such as the length of the chisel or the estimate of its volume, as the missing data cannot be ignored or set to zero. If we did that, the model would consider that zero value as the dimension and compare it with the values of other items for which we do have that information.

Several methods can be used to deal with this issue. The simplest one is to eliminate all samples with missing data or the missing feature altogether. However, in that case this solution would drastically reduce the size of the dataset. Moreover, removing any of the size features would deprive the model of valuable information, as the size of the item is considered to be an important feature.

A better alternative was to replace the missing information with a value that would have an effect as close to neutral as possible during the training of the model. An average of some sort is usually the value used. Several types of averages could be used. In this case, because the chisel size distribution is far from a *standard* or *normal* distribution and clearly contains samples that would be considered outliers if we did, the *median* seemed to be a reasonable value to use to replace missing values.

In any case, an additional model was also trained on a dataset (dataset 2) without these two quantitative features, as was yet another model using only one of them (Length), in order to be able to study the effect they have on the building of the model.

Numerical variables (*e.g.* Length) can be included in the database to be used for the analysis as they are, or following a simple normalisation of their values in the form of dividing the Length or Rod Volume value by the median of that feature. An additional database where these features are normalised using an average and a multiple of the standard deviation was also considered and the results compared.

Once the complete database had been encoded in a manner suitable for analysis, it was randomised and split into two parts. A training dataset was used to train the different models, while a test dataset that was not used during the training but instead used afterwards to check the reliability of the trained classification model and to compare the different models. For this work, the training set contained 90% of the samples and the test set the rest.

2.6 Computer Resources Required

Performing this type of model training used to be computationally demanding. Nowadays, however, an off-the-shelf computer is more than capable of performing this type of work. The computer we used to run these calculations has an Intel Core i7-4720HQ CPU, running at 2.60GHz with 4 physical cores (and, by hyperthreading, simulating 8 virtual cores) and 15.6 GiB of RAM. It runs 64-bit Ubuntu Linux 16.04 LTS and the mathematical programming environment Octave.[25]

3. Dataset Preparation

3.0.1 Database 1: Dataset Including Length and Rod Volume Estimates

This was the primary dataset prepared for the building of the model. It contains information from all qualitative features as well as the quantitative features Length and Rod Volume. Missing data on Length or Rod Volume were simulated using the *median* of that feature. The quantitative features were normalised using their median. This means that the normalised values were close to unity when they were close to the median of that feature.
Features used: Category; Type; Handle; Burr; Thread; Shoulder; Side; Section of Shaft; Bulges; Bevelling; Flaring of Edge; Edge Shape; Length of Chisel; Rod Volume.

3.0.2 Database 2: Dataset Not Including Quantitative Features Length and Rod Volume

A second dataset excluding both quantitative features, Length and Rod Volume, was used in order to study the combined effect of including these two features and also of using an inference method to deal with the missing values.

[25] EATON, J. W. et al., GNU Octave Version 4.0.0 Manual: a High-Level Interactive Language for Numerical Computations [online] [cit. 29 July 2019]. Available from https://octave.org/doc/interpreter/.

Features used: Category; Type; Handle; Burr; Thread; Shoulder; Side; Section of Shaft; Bulges; Bevelling; Flaring of Edge; Edge Shape.

3.0.3 Database 3: Dataset Including Quantitative Features Length and Rod Volume, Classical Normalisation

A third dataset including both quantitative features, Length and Rod Volume, was also used. In this case, as in Database 1, the missing data on Length or Rod Volume were simulated using the *median* of that feature. The difference in this case was that each of those features was then normalised using the average and standard deviation of the feature, that is by subtracting from each value the average of the feature and dividing the result by six standard deviations. In this way, we obtained a normalised value centred on zero.
Features used: Category; Type; Handle; Burr; Thread; Shoulder; Side; Section of Shaft; Bulges; Bevelling; Flaring of Edge; Edge Shape; Length of Chisel; Rod Volume.

3.0.4 Database 4: Dataset Including Quantitative Feature Length Only, Classical Normalisation

A fourth dataset including only Length as a quantitative feature was also used. As in the previous cases, the missing data on Length were simulated using the *median* of that feature. The feature was then normalised in the same manner as Database 3.
Features used: Category; Type; Handle; Burr; Thread; Shoulder; Side; Section of Shaft; Bulges; Bevelling; Flaring of Edge; Edge Shape; Length of Chisel.

3.1 Probability of Random Guess

In order to be able to establish the quality and reliability of the predictions of the models developed, it was first necessary to establish the probability of obtaining a correct prediction by chance. This provided a baseline against which to compare the results of the classification models developed.

This probability is obtained from the proportion of samples corresponding to each site and the probability that a random guess would predict the right site by chance. Since all four datasets, before splitting into the train and test sets, contained the same number and distribution of samples, the probability of a random correct prediction was the same: 17.25%.

4. Linear Classification Model

One linear classification model was trained on Database 1 using a *gradient descent* optimisation algorithm. The number of training iterations was limited to 500 for the final model. Regularisation (a procedure to avoid overfitting), was kept low (λ=0.1). The model was trained on the training set containing 90% of the database used and then tested on the test set containing the remaining 10% of data never seen by the model before. Once the model was trained and tested on unseen data, the percentage of correct predictions reached 66.3%. This proved a clear improvement with respect to a random prediction (17.25%).

5. Non-Linear Classification Model

5.1 Artificial Neural Network Regression

An artificial neural network is a non-linear regression method remotely related to the operation of biological neurons. The inputs $x_1 \ldots x_n$ to a neural node are operated over an activation function and transferred as inputs to the next neural layer, eventually producing the output Y (**Fig. 6**).

Different ANN architectures are possible with varying numbers of hidden layers and of nodes in each hidden layer as well as with a range of different activation functions. Commonly used activation functions include hyperbolic tangent, sigmoid and linear functions. Because of the non-linear nature of its transference function, a neural network can capture interactions between the inputs and output that would be impossible using a traditional linear regression model. ANNs are used both in regression and classification models.[26]

5.2 Risk of Overfitting. Regularisation.

Unfortunately, there are some difficulties involved in using non-linear model fitting methods and one needs to be aware of them. Precisely because the fitting of the model is performed automatically, there is a need to ensure that the model describes

[26] BHADESHIA, H. K. D. H. Neural Networks in Materials Science [online]. DOI: https://doi.org/10.2355/isijinternational.39.966; GAUDE-FUGAROLAS, D. Modelling of Transformations during Induction Hardening and Tempering [online] [cit. 29 July 2019]. DOI: https://doi.org/10.17863/CAM.14223; MACKAY, J. C. Information Theory, Inference and Learning Algorithms; NG, A. Machine Learning [online] [cit. 29 July 2019]. Available from https://www.coursera.org/learn/machine-learning.

the phenomenon of interest rather than the noise in the experimental data. It is a common mistake to fit increasingly complex models to a dataset and obtain very good error scores, only to discover later that the model is unable to describe unseen samples of the data (overfitting, or *high variance* fit, **Fig. 7c**). The opposite problem consists in having an overly simple model (*i.e.* a model that does not include all the relevant parameters) leading to a *high bias* fit (**Fig. 7a**).[27]

A degree of overfitting (the error when making predictions on the *test dataset* was clearly larger than the error on the *training set*) was detected in the ANN examples produced. *Regularisation* was used to avoid this problem. Without entering into excessive detail, regularisation is a method of reducing a high variance fit (overfit) of the model by penalising excess of complexity in it.[28]

The architecture of all the non-linear models built within this work uses sigmoid functions in the hidden units and a linear function in the output unit.

5.3 Non-Linear Classification Model 1, Including Both Quantitative Features

An initial model was produced using the dataset Database 1, which included both Length and Rod Volume features. Several architectures were tried for this model, with one hidden layer and a number of units in that hidden layer ranging from as many as the number of input parameters to ten times more. Because of the inherent risk of over-fitting involved in a non-linear architecture, the selection of the regularisation parameter was of special consequence. The regularisation parameter was tried within a range from $\lambda=0$ to $\lambda=5$. The number of iterations for training were usually 1,000, but up to 5,000 in some cases.

Several good architectures were found. Small variations could be also related to random starting values for the parameters of the network. The best model built contained 3 times as many hidden units as input parameters, with regularisation parameter $\lambda=0.1$ and training for 1,000 iterations. The optimisation algorithm used was developed by Carl Edward Rasmussen (library with the algorithm accessible in [29]). With the model thus obtained, the accuracy when making predictions on the

[27] BHADESHIA, H. K. D. H. Neural Networks in Materials Science [online]. DOI: https://doi.org/10.2355/isijinternational.39.966; GAUDE-FUGAROLAS, D. Modelling of Transformations during Induction Hardening and Tempering [online] [cit. 29 July 2019]. DOI: https://doi.org/10.17863/CAM.14223; MACKAY, J. C. Information Theory, Inference and Learning Algorithms; NG, A. Machine Learning [online] [cit. 29 July 2019]. Available from https://www.coursera.org/learn/machine-learning.
[28] Ibid.
[29] NG, A. Machine Learning [online] [cit. 29 July 2019]. Available from https://www.coursera.org/learn/machine-learning.

training dataset was 91.5%, and when tested on unseen data (test set), the percentage of correct predictions reached 75.9%. This, again, proved a clear improvement with respect to a random prediction on this database (17.25%), and some improvement also compared to the linear classification model (66.3%).

5.4 Additional Non-Linear Classification Models

Three additional non-linear models were produced in order to check the soundness of the model. The first one checked the validity of using the two quantitative features, Length and Rod Volume, even though we did not have data for all the samples (the missing data being sorted out as described earlier). On top of that, two different normalisation methods were tried, also as described earlier, and their effect analysed from the results of each model.

5.4.1 Non-Linear Classification Model 2, Not Including Quantitative Features

A second neural network-based model was trained on Database 2, a database without the Length and Rod Volume quantitative features. The aim was to compare the performance when these features are not included and to study the effect of using an inference method to resolve the missing data.

The best model, in this case, contained 3 times as many hidden units as input parameters, with regularisation parameter λ=0.2 and training for 1,000 iterations. With the model thus obtained, the accuracy when making predictions on the training dataset was 80%, and when tested on unseen data (test set), the percentage of correct predictions reached 71%. This again proved a clear improvement with respect to a random prediction on this database (17.25%), but a drop in performance with respect to the previous neural network classification model (75.9%), which included both quantitative features. It was inferred from this result that both quantitative features added valuable information to the model.

5.4.2 Non-linear Classification Model 3, Classical Normalisation, Length and Rod Volume as Quantitative Features

Another neural network-based model was trained on Database 3, a database with normalised Length and Rod Volume quantitative features. With this set we could study the effect of the use of classical-average and standard-deviation normalisation. The best model in this case contained 3 times as many hidden units as input parameters, with regularisation parameter λ=0.2 and training for 1,000 iterations. With the model thus obtained, the accuracy when making predictions on the training dataset was 81.83%, and, when tested on unseen data (test set), the percentage of correct predictions reached 62.65%. This again proved a clear improvement with respect to a random prediction on this database (17.25%), but a drop in performance compared to the first neural network classification model (75.9%), which included both quantitative features and a simpler normalisation method.

5.4.3 Non-Linear Classification Model 4, Classical Normalisation, Only Length as a Quantitative Feature

Another neural network-based model was trained on Database 4, on a database with the normalised Length quantitative feature (but not Rod Volume). With this set we could study the effect of the use of the classical average and standard deviation normalisation. The Length parameter column contains more data than Rod Volume, so fewer substitutions for missing data were needed.

The best model in this case contained 2 times as many hidden units as input parameters, with regularisation parameter λ=0.3 and training for 1,000 iterations. With the model thus obtained, the accuracy when making predictions on the training dataset was 81.70%, and when tested on unseen data (test set), the percentage of correct predictions reached 63.86%. This again proved a clear improvement with respect to a random prediction on this database (17.25%), but a drop in performance compared to the first neural network classification model (75.9%), which included both quantitative features and a simpler normalisation method.

5.4.4 Comparison of all Classification Models Produced

Four different models have been trained. All of them provide good results when providing predictions as to the origin of some items with respect to both the training dataset and to the unseen testing dataset. All of them provide similar or better predictions than the linear classification model. The inclusion of both quantitative features, Length and Rod Volume, produces an improvement in the quality of the predictions, despite some data missing in both features that had to be inferred. On the other hand, the use of simpler normalisation of the quantitative features produces a better description of the data by the model than when a more elaborate normalisation method is applied. The model produced using Database 1 shows a clearly superior performance to the others (including the linear model) and is therefore the one that has been used as the main model in the remaining part of this work.

6. Application: Classification of Items of Unknown Origin

The database used included five samples for which the site of origin was not known, as well as several more (61) that supposedly originated from Giza, but on which detailed information was unknown. With all due regard to the difficulties involved, an attempt was made to use the best non-linear classification model produced to obtain a suggestion of the possible origin for each of these items and the results were analysed.

The first difficulty for this operation, the more important one, was that the items of unknown origin need not come from any of the possible origin sites contemplated in the model. Additionally, the parameters used to define each item might or might not be sufficient to differentiate clearly between items of different origin. Both of these problems are discussed below.

Interrogated about the possible origin of these items, each of the non-linear models produces a prediction based on comparing the likelihood of belonging to one of the 11 possible origins the model contemplates (basically, those included in the database used to train the model). These predictions needed to be studied carefully, taking into account the way the model produces that result rather than only the result "*per se*".

6.1 Criteria Used by a Classification Model to Make Predictions

A basic classification model produces an output that makes it possible to distinguish between two *states* or cases. Typically, they are of the sort "*is/belongs to*" and "*is not/does not belong to*". This is referred to as binary classification. However, some problems require categorisation into multiple classes ("belongs to A", "belongs to B", "belongs to C", *etc.*). A different approach is needed in these cases. A simple approach to the multi-classification problem is to use a *One-vs-all* criterion. With this approach, the classification model produces an estimate of the likelihood of an item to belong to one case compared to the likelihood that it belongs to any of the other cases. Such estimates are produced for each of the cases, and the one presenting the highest likelihood is chosen as the final prediction of the model.

6.2 Criteria Used to Estimate Reliability of Predictions

As described in the previous section, the classification model alone provides a suggestion as to the possible Site (or Part of Site) of origin of the sample under analysis. However, it is important to bear in mind how the selection process works and to establish additional criteria to determine which predictions are sound and which show an option that is only marginally better than another one.

For instance, in a case like the example shown in **Fig. 8**, a clear suggestion that sample item 824 originated from site 7 was offered by the classification model.

In contrast to that, **Fig. 9** shows how the model is unable to suggest with any certainty the origin of sample item 841. However, as site 3 has a marginally higher likelihood, it is the result returned by the model.

To avoid situations of the latter type, the following additional criteria were defined to determine the reliability of the model's suggestions.

The first and main criterion is that the highest likelihood is higher by at least 0.8 than all the others combined. A *softer* secondary criterion is that while the highest likelihood is higher than 0.8, the difference between this one and all the rest combined is higher than 0.5. As the likelihoods provided by the model always range from zero to one, both criteria are rather stringent.

6.3 Predictions on the Test Set

6.3.1 Test set: Distribution of Sites and Predictions

Fig. 10 and **11** show the distribution of sites of the items in the testing dataset and the distribution of predictions obtained from model 1 using the test data, respectively.

6.3.2 Accuracy of Predictions in the Test set and the Probability of a Random Guess

The probability of making a correct random guess when making predictions on the test set was 19.90%. The accuracy obtained using the non-linear model 1 to make predictions on the test set was 75.90%.

6.4 Predictions on Samples of Unknown Origin

All four non-linear classification models were used to produce suggestions on the origin of items for which no original site information (or only incomplete information) was available. The distribution of predictions made by model 1 is shown in **Fig. 12**.

Although most items in the unknown origin category were believed to originate from some of the site parts of Giza, we observed that the predictions of the model propose that a fraction of them come from other sites.

However, having applied the reliability criteria to these suggestions as described in section 6.2, we can see that some of the model's suggestions seemed to be highly reliable (and often coincident with the suggestions of all other models), while many were less reliable (at least according to the criteria described in section 6.2). Of a total of 66 samples of unknown origin, the 28 that were classified reliably are listed in **Table 4**.

Nevertheless, some of the suggestions considered reliable remain intriguing. In particular, all four models suggest that a number of items could originate from Abusir South (Site 2), and another group of items from Abydos (Site 4). The interesting fact is that it was expected that most of the items without information (or with only partial information) about their origin would be related to one of the Giza sites (Sites 6 to 10). The suggestions from the models were considered reliable in the sense that they fulfil one or both criteria described in section 6.2. Moreover, in all these cases all four models gave the same suggestion. This result calls for studying those items in more detail.

7. Discussion

The results obtained using the classification model developed within this work need to be divided into two cases. On the one hand, we have a series of predictions, suggestions as to the origin of a number of items that seem to conform with the authors' expectations, even though the knowledge of the context is important also in these cases. Another element that needs to be taken into account is the function of copper workshops, which means that objects from different site parts would be similar in the same period if produced by the same craftsmen or by craftsmen with a similar mental template of the model tool. Then there are some predictions which at first glance could be regarded as intriguing and possibly even incorrect. We will comment on both cases.

In the case of fully preserved model chisel blades, the model points to the most probable site of origin of these chisels from the excavations of H. Junker at Giza. We know of several tombs where models were found, but the exact identification of the tombs was not possible in the reserve of the Kunsthistorisches Museum in Vienna (**Fig. 13**). The mathematical model enables us to pinpoint the most probable places of origin for these models, but contextual information is needed to be able to evaluate the results. Junker gave measurements of his finds from the Southern Field and as they apparently do not conform with our assemblage, the most reasonable candidates can be supposed to come from the Western Field.

Chisels of IDs 824 to 835 from presumed Context G 124 were attributed to various sites by their properties, the most frequent being the Western Field, although only in three cases out of eleven. The spectrum of shapes of not only chisels but also adzes, saws and razor blades are similar, albeit not identical to shapes from Dynasty-5 contexts at Giza currently stored in the Museum of Fine Arts, Boston and excavated from tombs neighbouring to Junker's excavations.[30] The same observation is valid for a chisel from Context G125, ID 851.

The Western Field was determined once again for chisels from Context G129, where the chisels are rather thin and thus might be datable to Dynasty 5 or Dynasty 6 contexts. The Central Field is impossible for ID 914 and the Southern Field rather improbable for ID 908. Thus, if we compare the data from Junker's publications with the model's predictions, the best candidates for the assemblages in question are tomb G 2156 with a "range of the usual model tools" and thus probably Context G124. Candidates for smaller contexts are tombs G 5350 and S 4237. Both the contextual evidence and the predictive model give indications that these objects were found at the Western Field.

Similarly, in the case of Site 10, the prediction has a chronological basis, because the predicted chisels are similar to those found in a dated context from Cemetery G I S from early Dynasty 4. This is the reason why the mathematical model predicted an affinity of chisels ID375, from Nubia, and ID379, with unknown provenance. For all these items, the classification model's predictions provide sensible suggestions as to the origin of those items.

On the other hand, there are other predictions that seem to point to excavations sites that are very unlikely to be the origin of the items in question. Does that mean that the classification model is wrong? Before we dismiss the potential of the classification model, we should consider the way it works. During the training process, the classification model extracts as much information as possible from the training database; then, during prediction, it uses that information to produce its prediction. That prediction is based on the similarity of the item under study to each of the categories generated during the training of the model. We must be aware, however, that any biases contained in the training database are transferred into the model.

What we encounter in the case of those unusual predictions is not that the model is suggesting the wrong site of origin, but that it is suggesting the site with which that item has a closer similarity from the point of view of the data provided. In our case, the probable reason why fragmentarily preserved chisel blades tend to be classified as coming from Abusir South is that in both cases, the descriptions of the items (both in the training set and the studied item) are similarly fragmentary. This finding is consequently explained by the higher number of

[30] ODLER, M. *Old Kingdom Copper Tools and Model Tools*, Fig. 39.

fragments from Abusir South described in the database; full-size models were documented above all from the other sites. Therefore, the model reliably assigns items with fragmentary information in the category that is characterised by having fragmentary data.

This reminds us that in order to make use of the ample benefits of advanced mathematical modelling, we need to understand their operation in sufficient depth. Otherwise, if these techniques were to be used carelessly, the results obtained might become meaningless.

8. Conclusions

Several databases on Old Kingdom copper items were considered as to their suitability for the application of machine learning or data analysis techniques. A database of chisels was selected, and a smaller dataset extracted from it was used to train several linear and non-linear classification models. All these models were able to *classify* the items according to their origin.

The non-linear models are based on an artificial neural network (ANN). The classification models obtained using this technique produced better predictions than the linear model. The best performing of the non-linear ANN classification models was used to suggest (classify) the origin of some items for which that information is unknown or incomplete. In several cases, it produced suggestions that are considered reliable. This was not always the case, however. The difference between reliable or unreliable suggestions has been determined using stringent mathematical criteria applied to the outcome of the model. Nevertheless, a number of reliable suggestions produced by the model present intriguing possibilities that encourage further study of some of the items in the original database.

The work will proceed in a broader chronological time span of Egyptian history, including all chisels from the Fourth to the Second Millennia BC, in order to describe general trends existing in the development of chisels. For an outsider, ancient Egyptian tools are almost identical throughout their history,[31] yet significant changes have been observed even within a single period, the Old Kingdom.[32] A broader set will make it possible to pinpoint changes in the known tools.

[31] BRYSBAERT, A. Introduction. In BRYSBAERT, A., GORGUES, A. (eds.). *Artisans Versus Nobility? Multiple Identities of eElites and Commoners Viewed through the Lens of Crafting from the Chalcolithic to the Iron Ages in Europe and the Mediterranean*, p. 22.

[32] ODLER, M. *Old Kingdom Copper Tools and Model Tools*.

The proposed method could also be applied to a possible determination of unprovenanced pieces, or at least to estimate the most probable place of origin for such objects in museum collections.

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Captions of figures and tables

Fig. 1: Full-size functional Old Kingdom chisels (context numbers in the catalogue of the publication, edited according to ODLER 2016, Fig. 20).
Fig. 2: Types and variants of Old Kingdom chisels ODLER 2016, Figs. 90, 91).
Fig. 3: Old Kingdom copper model tools and vessels from the collection of the Kunsthistorisches Museum in Vienna, most probably coming from excavations by Hermann Junker at Giza (IDs of the chisels mentioned in the text added according to ODLER 2016, Fig. 47).
Fig. 4: Chisels in the archaeological contexts of Old Kingdom Egypt (Martin Odler in qGIS software, background Natural Earth).
Fig. 5: Types of chisels from various parts of the Giza necropolis (Martin Odler in qGIS software, background Open Street Map shapefiles).
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Table 1: Contexts with copper finds from the excavations by Hermann Junker at Giza.
Table 2: Chisel types in the archaeological contexts of Old Kingdom Egyptian sites.
Table 3: Types of chisels from various parts of the Giza necropolis.
Table 4: Predictions meeting the reliability criteria.

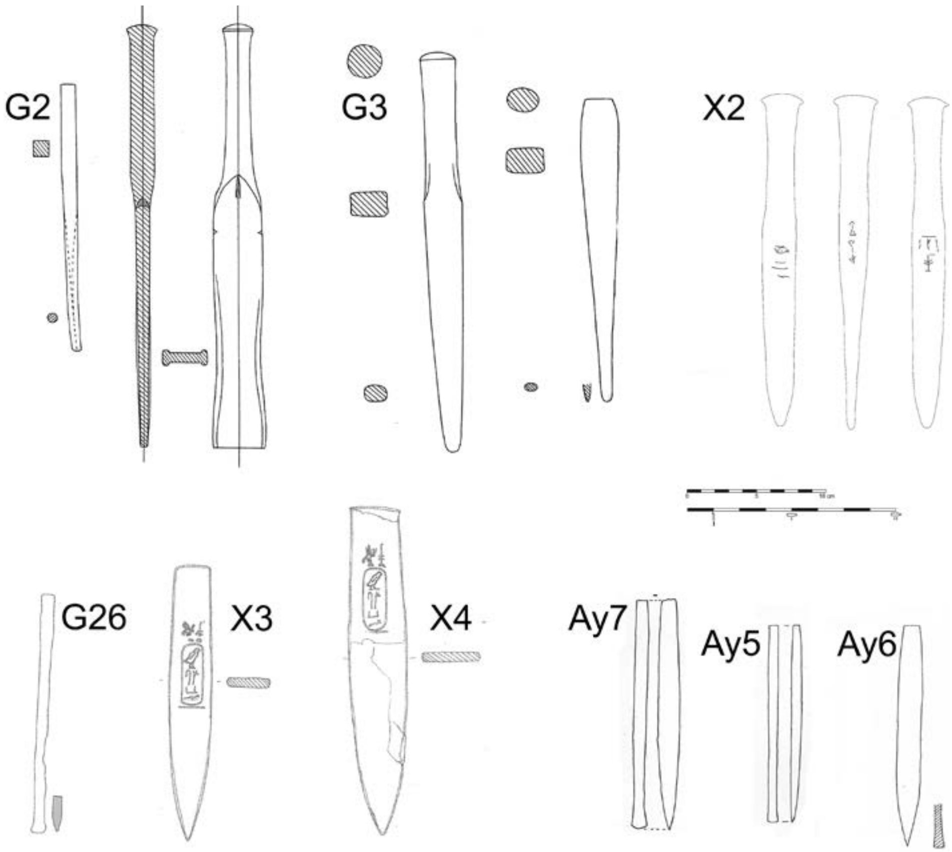

Fig. 1: Full-size functional Old Kingdom chisels (context numbers in the catalogue of the publication, edited according to ODLER 2016, Fig. 20).

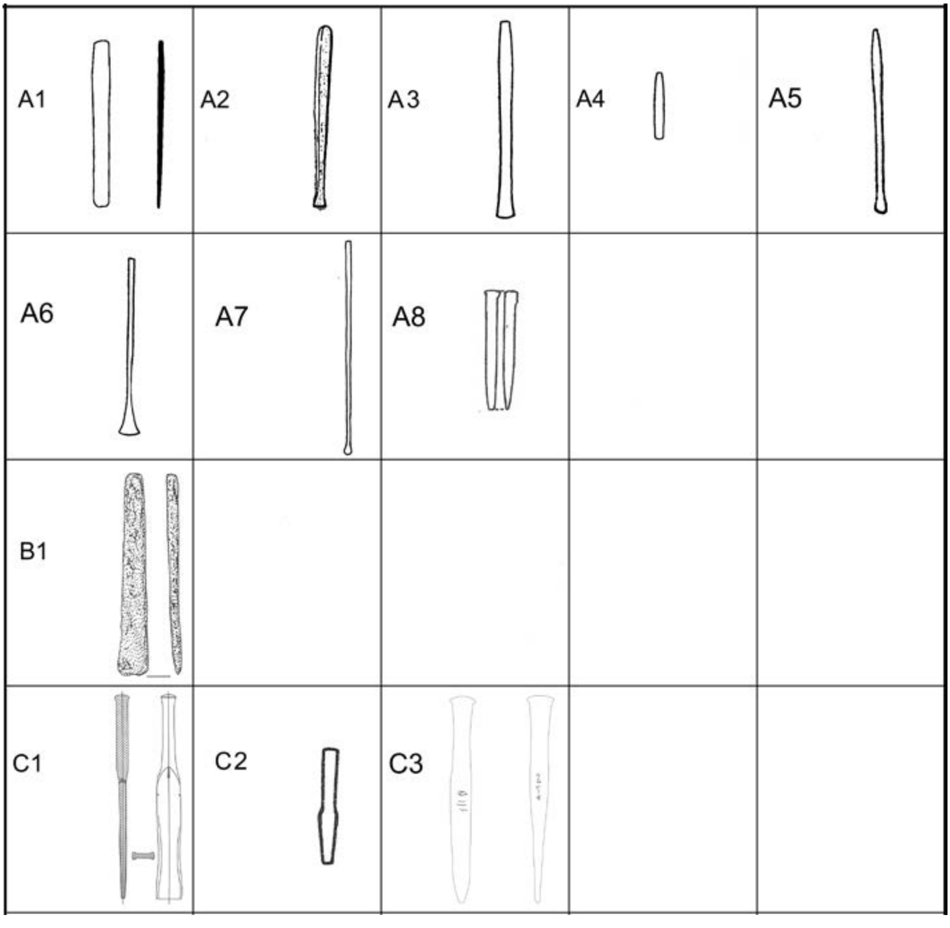

Fig. 2a: Types and variants of Old Kingdom chisels, ODLER 2016, Figs. 90, 91).

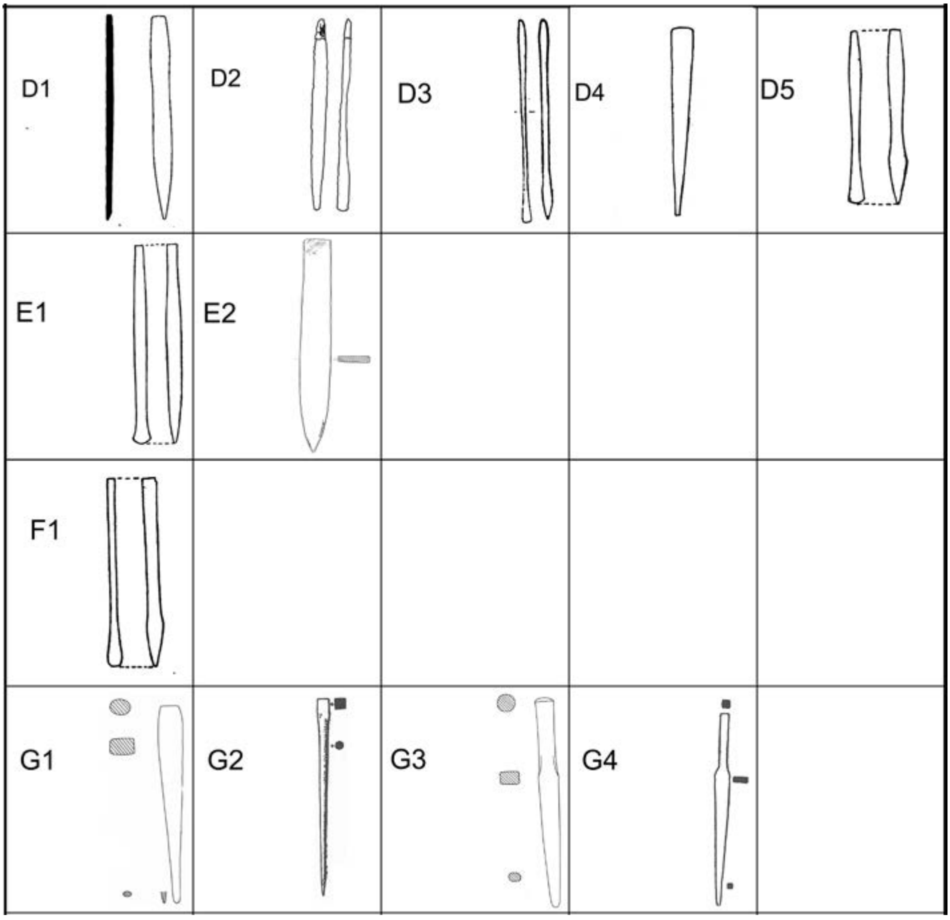

Fig. 2b: Types and variants of Old Kingdom chisels, ODLER 2016, Figs. 90, 91).

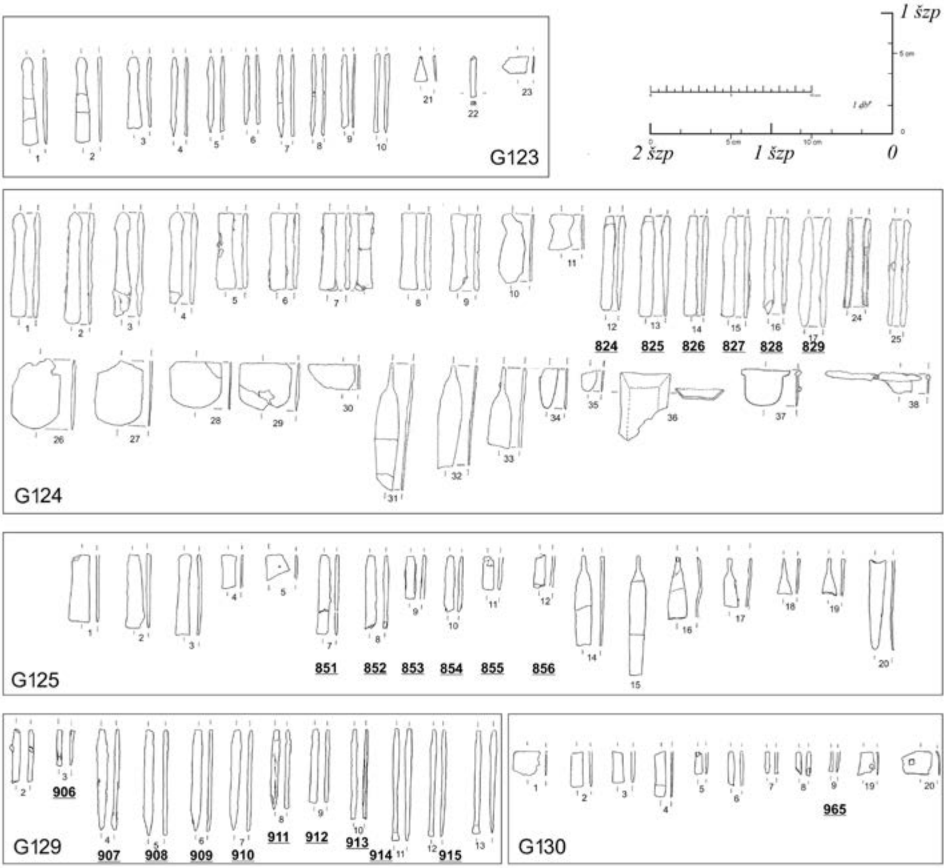

Fig. 3: Old Kingdom copper model tools and vessels from the collection of the Kunsthistorisches Museum in Vienna, most probably coming from excavations by Hermann Junker at Giza (IDs of the chisels mentioned in the text added according to ODLER 2016, Fig. 47).

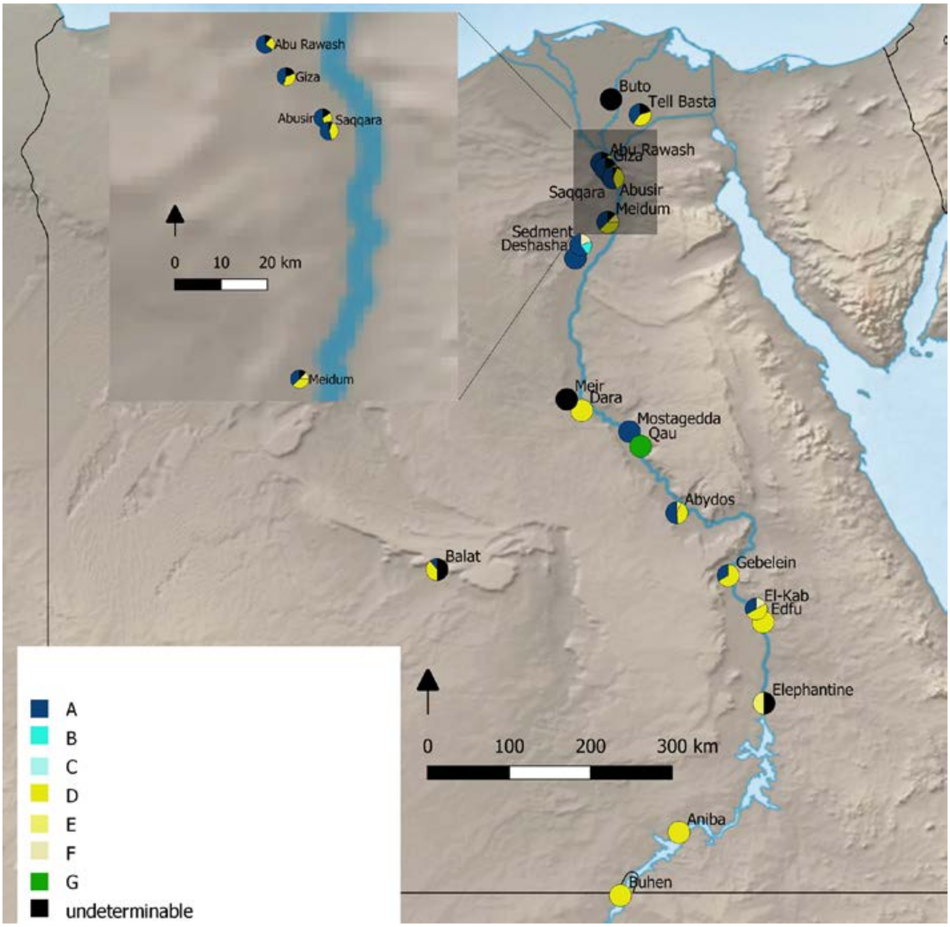

Fig. 4: Chisels in the archaeological contexts of Old Kingdom Egypt (Martin Odler in qGIS software, background Natural Earth).

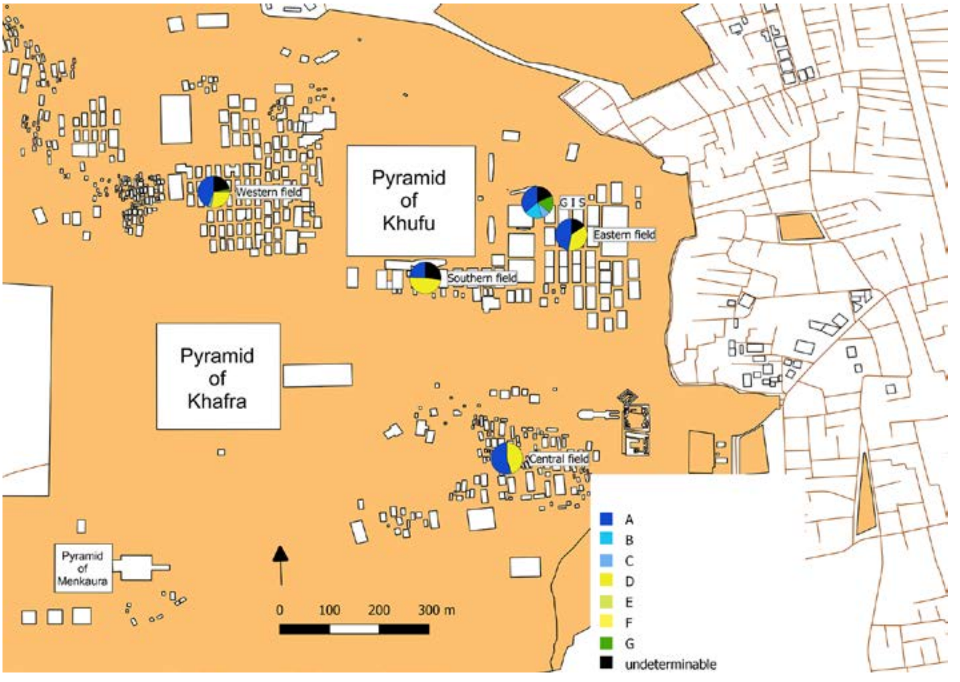

Fig. 5: Types of chisels from various parts of the Giza necropolis (Martin Odler in qGIS software, background Open Street Map shapefiles).

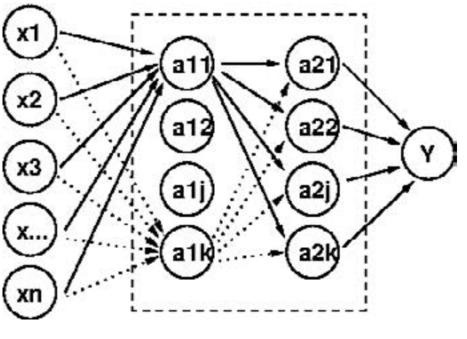

Fig. 6: Schematic description of the architecture of an artificial neural network (ANN). An ANN consists of a black box within which one or more layers of hidden nodes compute the prediction Y from a set of input parameters $x_1 \ldots x_n$.

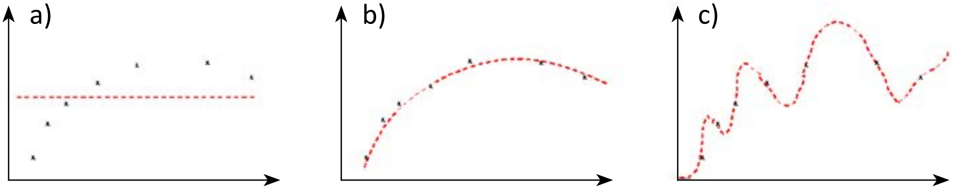

Fig. 7: Finding the right balance of model fitting. a) High bias model (underfit). b) Balanced fit. c) High variance model (overfit).

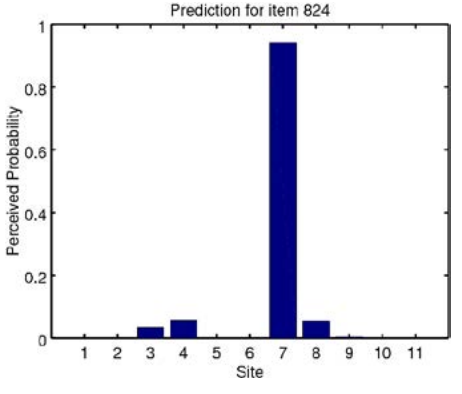

Fig. 8: Example of an output of the classification model in which one of the options shows a clearly higher likelihood than the rest.

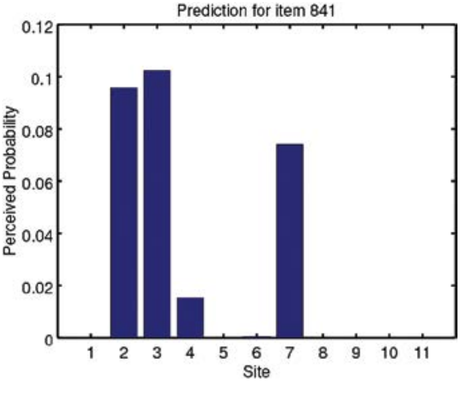

Fig. 9: Example of an output of the classification model in which none of the options shows a clearly higher likelihood than the rest.

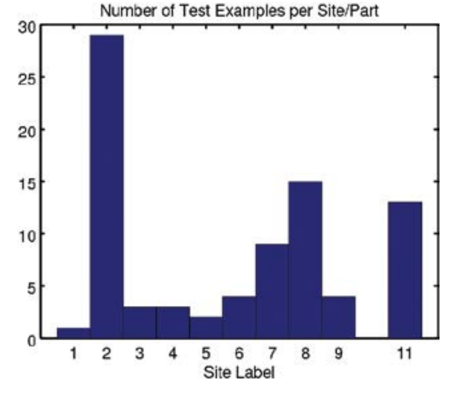

Fig. 10: Distribution of the sites in the test set.

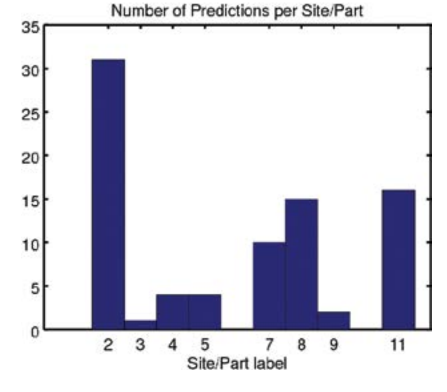

Fig. 11: Distribution of the sites when making predictions on the test set.

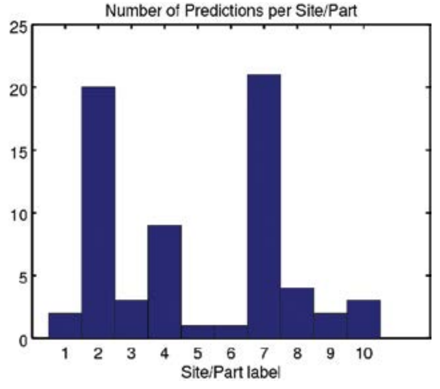

Fig. 12: Distribution of the predictions by model 1.

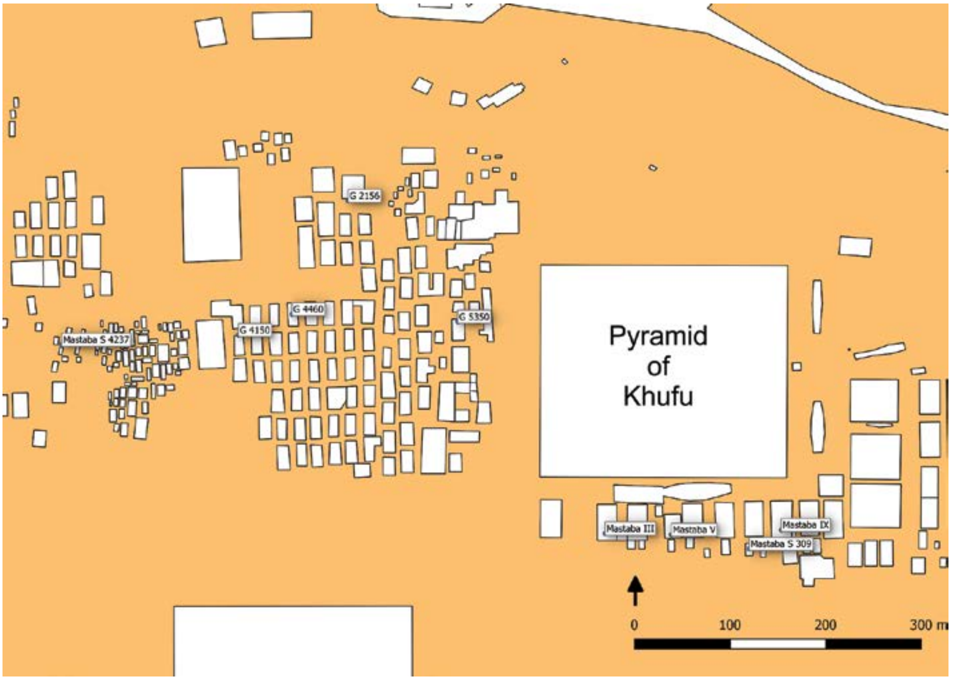

Fig. 13: Western and Southern Fields of Giza, with tombs with finds of copper model tools of unknown current location marked (Martin Odler in qGIS software, background Open Street Map shapefiles).

Table 1: Contexts with copper finds from the excavations by Hermann Junker at Giza.

Site	Part of site	Structure	Owner	Gender	Social status	Period	Bibliography	Present location	Type of context	Description of context
Giza	Western field, cemetery G 4000	G 4150, secondary shaft in the north	*Jw-nw*	man	overseer of the phyles of Upper Egypt	Old Kingdom, Dynasty 4, the reign of Khufu	Junker (1929, 181)	unknown	secondary	„Scheinwerkzeuge aus Kupfer: Bruchstücke von Meißelblatt und von runder Stange.“
Giza	Western field, cemetery G 4000	G 4250	unknown	unknown	–	Old Kingdom, Dynasty 4, the reign of Khufu	Junker (1929, 194, Abb. 17: 1, 11–13)	unknown	secondary	Most probably from the burial chamber.
Giza	Western field	G 4460	unknown	unknown	unknown	Old Kingdom, Dynasty 4, the reign of Khufu	Junker (1929, 205)	unknown	unknown	„kleine Kupferbeigaben“
Giza	Western field	G 4360	*mry-ḥtp=f*	man	judge and administrator	Old Kingdom, Dynasty 4 to 5	Junker (1929, Abb. 17: 2–10, 14)	unknown	secondary	No information.
Giza	Western field	G 2156	*K3(=j)-n(.j)-n-swt* II	man	perhaps son of prince	Old Kingdom, Dynasty 5, the reign of Nyuserra	Junker (1938, 150)	unknown	secondary	Found in partially robbed burial chamber: „...eine reihe kleine Kupferwerkzeuge der üblichen Art.“
Giza	Western field	G 4970	*ḫntt-k3*	woman	wife of *nśwt–nfr*	Old Kingdom, Dynasty 5, the reign of Sahura	Junker (1938, 166)	Kunsthistorisches Museum, Wien, Austria	secondary	Found in the filling of the northern shaft, belonging to the wife of *Nsw–nfr*. The metal finds have been found in the debris of the northern shaft in the tomb, together with a fragment of a red bowl. The fragments of combed ware amphora enabled to reconstruct the shape of the complete vessel. K. Sowada collected various datings of the vessel, early to middle Dynasty 5 dating is the most frequent for the tomb itself. As the vessel was not identified in any contemporary museum collection, it cannot be decided whether it was genuine import from Levant or an Egyptian imitation. Both model adze blades were much corroded. Besides them, the assemblage contained a fragment of chisel, saw blade and possibly also a fragmentarily preserved axe blade.
Giza	Western field, cemetery en echelon	G 5470	*Rʿ(.w)-wr* II	man	judge and priest	Old Kingdom, Dynasty 5, late	Junker (1938, 226)	Kunsthistorisches Museum, Wien, Austria	secondary	Found in the partially robbed main burial chamber.

Table 1: Contexts with copper finds from the excavations by Hermann Junker at Giza – continued 1

Site	Part of site	Structure	Owner	Gender	Social status	Period	Bibliography	Present location	Type of context	Description of context
Giza	Western field	Mastaba of Seneb	*snb*	man	director of dwarfs in charge of dressing, god's sealer of the Wenherbau-ship, priest of Wadjet lady of the Lower Egyptian shrine, overseer of libations (?), companion of the house; and granite offering stone	Old Kingdom, Dynasty 6, end	Junker (1941, 124, Taf. XX)	Roemer-Pelizaeus Museum, Hildesheim, Germany	secondary	Found in the burial chamber. Sifting of the refuse layer after robbers, tear-shaped pendants of wooden core and covered with gold foil. Copper split pins „aus dem Schutt der Mastaba".
Giza	Western field, cemetery G 2100	Mastaba of Neferihy	*nfr-ihy*	man probably	funerary priest	Old Kingdom, Dynasty 6	Junker (1943, 161-162, Abb. 55)	Kunsthistorisches Museum, Wien, Austria	secondary	Found in the robbed shaft, the only shaft in the tomb
Giza	Western field, cemetery en echelon	G 5350 (Mastaba S 846/847)		undetermined		Old Kingdom, Dynasty 5, middle	Junker (1944, 185)	unknown	secondary	Found in the burial chamber of Shaft 846: „Bruchstücke von Werkzeugmodellen".
Giza	Western field	Mastaba of Ptahhetep, Shaft 890A	*ḥtp–Ptḥ*	man	judge and priest	Old Kingdom, Dynasty 6	Junker (1944, 228, Abb. 93)	Kunsthistorisches Museum, Wien, Austria; Roemer-Pelizaeus Museum, Hildesheim, Germany (copper)	secondary	Found in the partially robbed burial chamber of Ptahhotep, shaft 890A.
Giza	Western field	Mastaba S 309-316, Shaft 316	unknown	man	–	Old Kingdom, Dynasty 6	Junker (1944, 52–54, 58–60, Abb. 19, 24)	Kunsthistorisches Museum, Wien, Austria	primary	Model tools found in the southern part of the chamber, partly under travertine vessels. Headband found near the skull and deeper in front of chest. The sketch published by Grajetzki (2000, fig. 23).
Giza	Western field	Mastaba S 309-316, Shaft 315	unknown	woman probably	wife of the owner of tomb most probably	Old Kingdom, Dynasty 6	Junker (1944, 61–62, Taf. XI)	Kunsthistorisches Museum, Wien, Austria	secondary	Found in eastwards from the burial and on the southern end of the burial goods, in the ceramic bowl and on the floor of the chamber.
Giza	Western field	Mastaba S 309-316	unknown	woman probably	–	Old Kingdom, Dynasty 6	Junker (1944, 62, Taf. XIIIb)	Roemer-Pelizaeus Museum, Hildesheim, Germany	secondary	Found in the partially robbed burial chamber. Found in the partially robbed burial chamber. Find in the bottom of the shaft.
Giza	Western field	Shaft 688	*Jry-n-ʿḫ.ty*	woman	most probably spouse of the tomb owner	Old Kingdom, late / First Intermediate period	Junker (1947, 153, Abb. 75)	unknown	primary	Found on the left shoulder of deceased. The shaft is located southwards from the main shaft.
Giza	Western field	Mastaba of Shafts 4215 and 4314	*Mn-jb*	woman	priestess	Old Kingdom, Dynasty 6, end	Junker (1950, 22, 218, Taf. 6c)	Roemer-Pelizaeus Museum, Hildesheim, Germany	secondary	Found in the shaft/serdab 4215, together with small stone vessel for ointment/cosmetics.

Table 1: Contexts with copper finds from the excavations by Hermann Junker at Giza – continued 2

Site	Part of site	Structure	Owner	Gender	Social status	Period	Bibliography	Present location	Type of context	Description of context
Giza	Western field	Mastaba S 4237, north of Mastaba of Khnumhotep II	unknown	undetermi-ned	unknown	Old Kingdom, Dynasty 6	Junker (1950, 22)	unknown	secondary probably	Found in the shaft 4237: „reste von Kupferinstrumenten".
Giza	Southern field	Mastaba G I S 46	*ẖnmw-nfr*	man	royal hairdresser	Old Kingdom, Dynasty 6	Junker (1951, 111)	unknown	secondary	Wide needle with a rolled head.
Giza	Southern field	Mastaba V (Junker) / G IV S (Reisner) / Lepsius 52	*N(j)-ʿnḫ-Rʿ.w*	woman probably	wife of tomb owner	Old Kingdom, Dynasty 4, the reign of Menkaura	Junker (1951, 161)	unknown	secondary	Found in the southern shaft, which was the second biggest and most probably belonged to the wife of owner. Other material (pottery, stone vessels), both in Vienna and Hildesheim.
Giza	Southern field	Mastaba with Shafts 125/157	unknown	undetermi-ned	–	Old Kingdom, Dynasty 6	Junker (1951, 174)	Roemer-Pelizaeus Museum, Hildesheim, Germany	secondary	Found in the burial chamber of the shaft 125, main burial chamber of tomb.
Giza	Southern field	Mastaba with Shafts 309/312	unknown	man probably	–	Old Kingdom, Dynasty 5 and 6	Junker (1951, 186)	unknown	secondary	Found in the main burial chamber of shaft 309, model tools, axe (4.5 cm wide) and two chisels (7 and 6.5 cm long respectively).
Giza	Southern field	Mastaba III (Junker) / G II S (Reisner)	*kꜣ(=j)-m-nfr.t*	man	royal chamberlain	Old Kingdom, Dynasty 4, the reign of Menkaura	Junker (1951, 37)	unknown	secondary	Chisel (9 cm long) and another blade (6.1 cm long) found.
Giza	Southern field	Mastaba IX	*sẖm-kꜣ*	man	chamberlain, judge and priest	Old Kingdom, Dynasty 5 late or 6	Junker (1953, 12)	unknown	secondary	Found in the southern shaft, frag-ments of three chisels. Some finds in Hildesheim.
Giza	Southern field	Mastaba Lepsius 55	*Ny-ʿnḫ-Rʿ(.w)*	man	priest	Old Kingdom, Dynasty 5 to 6	Junker (1953, 82, Abb. 46, Taf. IX: c, d)	Kunsthistorisches Museum, Wien, Austria; Roemer-Pelizaeus Museum, Hildesheim, Germany (copper)	secondary	Found in the main northern shaft with burial chamber.

Table 2: Chisel types in the archaeological contexts of Old Kingdom Egyptian sites

Site	A	B	C	D	E	F	G	H	undeter-minable	Total
Abu Rawash	11	0	0	4	0	0	0	0	2	17
Abusir	161	0	1	94	1	0	0	0	47	304
Abydos	23	0	0	19	3	0	0	0	0	45
Aniba	0	0	0	1	0	0	0	0	0	1
Balat	2	0	0	7	0	0	0	0	9	18
Tell Basta	2	0	0	2	0	0	0	0	1	5
Buhen	0	0	0	1	0	0	0	0	0	1
Buto	0	0	0	0	0	0	0	0	1	1
Dara	0	0	0	1	0	0	0	0	0	1
Deshasha	1	0	0	0	0	0	0	2	0	3
Edfu	0	0	0	2	0	0	0	0	0	2
Elephantine	0	0	0	0	1	0	0	0	1	2
El-Kab	2	0	0	3	0	1	0	0	0	6
Gebelein	1	0	0	2	0	0	0	0	0	3
Giza	176	2	6	142	2	1	6	2	71	408
Qau	0	0	0	0	0	0	1	0	0	1
Meidum	3	0	0	3	1	0	0	0	1	8
Meir	0	0	0	0	0	0	0	0	14	14
Mostagedda	1	0	0	0	0	0	0	0	0	1
Saqqara	54	0	0	38	1	0	0	0	5	98
Sedment	3	1	0	0	0	1	0	0	0	5
Unknown	0	0	1	0	1	0	1	0	0	3
Total	440	3	8	319	12	3	8	4	152	947

Table 3: Types of chisels from various parts of the Giza necropolis

Part of site	A	B	C	D	E	F	G	undeter-minable	Total
Central field	65	0	1	54	0	0	0	0	120
Eastern field	9	0	0	7	0	0	0	3	19
G I S + Menkaura	4	2	1	0	0	0	2	2	11
Southern field	9	0	0	18	0	0	0	10	37
Western field	40	0	3	25	1	0	2	20	91
Total	127	2	5	104	1	0	4	35	278

Table 4: Predictions of the chisel provenance meeting the reliability criteria

chisel ID	Predicted site
375	10 – Giza G I S
379	10 – Giza G I S
824	7 – Giza: Western field
825	2 – Abusir South
827	7 – Giza: Western field
829	7 – Giza: Western field
831	8 – Giza: Central field
832	2 – Abusir South
833	4 – Abydos
835	2 – Abusir South
844	2 – Abusir South
845	2 – Abusir South
846	2 – Abusir South
847	2 – Abusir South
849	2 – Abusir South
850	7 – Giza: Western field
851	7 – Giza: Western field
856	2 – Abusir South
904	7 – Giza: Western field
906	7 – Giza: Western field
908	9 – Giza: Southern field
910	7 – Giza: Western field
914	8 – Giza: Central field
915	4 – Abydos
965	7 – Giza: Western field
966	2 – Abusir South
967	2 – Abusir South
973	2 – Abusir South