An adaptive algorithm for detecting double stars in astrometric surveys

Mikhail V. Sazhin, Valerian Sementsov, Sergey Sorokin, Dan Lubarskiy, and Alexander Raikov

1 Sternberg Astronomical Institute of Lomonosov Moscow State University, Universitetsky pr., 13, Moscow 119234, Russia
2 Tver State University, Zhelyabova 33, Tver, Russia
3 Scienteco, Inc., Boston, MA
4 Institute of Control Sciences, Russian Academy of Sciences

Submitted to AJ

ABSTRACT

The paper develops a method for detecting optical binary stars based on the use of astrometric catalogs in combination with machine learning (ML) methods. A computational experiment was carried out on the example of the HIPPARCOS mission catalog and the Pan-STARRS (PS1) catalog by applying the suggested method. It has shown that the reliability of predicting a stellar binarity reaches 90-95%. We note the prospects and effectiveness of creating a proprietary research platform — Cognotron.

Keywords: Binary stars (154) — Fundamental parameters of stars (555) — Astroinformatics (78) — Convolutional neural networks (1938) — Random Forests (1935)

1. INTRODUCTION

The purpose of this work is to increase the accuracy of estimating the ratio of the number of binaries over single stars by applying artificial intelligence (AI) methods to the classical astronomical techniques.

Binary stars form dynamic systems that rotate under the gravitational attraction around a common center of masses. Binary stars are subdivided into visual binary stars, spectral binary stars, and eclipsed variable stars (Hilditch 2001, pp. 17-21). Methods of their detection are, therefore, divided into astrometric, spectral, and photometric. The development of classical methods of astronomical measurements calls for increasingly complex models, which may include more than ten free parameters per object. As a result, the proportion of discovered stars demonstrating non-linear motions is constantly increasing and, accordingly, the risk of an erroneous estimation of the ratio of binary and single stars is growing. In addition, the classical methods of processing astrometric measurements suffer from the “curse of dimensionality” when the computational costs to determine the nonlinear and free parameters grows exponentially with respect to their number.

In this paper, it is proposed to supplement the classical methods of estimating the aforementioned ratio with ML methods. The latter allow to work with a set of poorly defined parameters and reduce
the exponential growth of the volume of calculations, arising from their number, to polynomial. However, modern ML methods, as it is well known, do not always enable us to get an explanation of the results obtained. For the purpose of this paper, this is not an obstacle, since the verification of the results derived from the data by ML, as in the classical case, is carried out based on direct observations.

Applications of ML have an appealing potential, which is constantly increasing, primarily due to the development of ML methods and analytical methods of processing big data, as well as the growth of computer power. New versions of ML are being introduced, and the computing capabilities for their implementation are increasing. The development of methods is heading in the direction of providing opportunities to self-study, adapt to the dynamics of the external environment, solve interdisciplinary tasks, plan, analyze, give explanations, consider the subjective, non-local and wave aspects of the behavior of the research objects Wang et al. (2018); Raikov (2021).

As an example of a successful application of ML in astronomy, one can mention the work Becker et al. (2020), presenting a classifier of astronomical events in real time for Automatic Learning System for the Rapid Classification of Events (ALeRCE). The article Carrasco-Davis et al. (2021) discusses photometric and spectroscopic observations of rapidly variable sources formed after the explosion of an astronomical object. To classify signals from the nuclei of galaxies, supernovae, asteroids, etc. Convolutional Neural Network (CNN) is used. At the same time, metadata is added to astronomical images in the form of a priori known functions and indicators, which helps achieve a high level of accuracy (≈ 94 %). There are two types of classification methods — based on a template and a light curve. The first is able to distinguish a richer taxonomy of events, the second uses only the first event warning. The classification of events by templates is based on the use of CNN Carrasco-Davis et al. (2021). CNN input requires images and metadata about the properties of objects from various catalogs. The standard shape of the event template is 63 x 63 pixels. The list of alert metadata includes about 15 indicators.

The authors of ALeRCE (2022) proposed a template-based classification method for distinguishing five different classes of events within the framework of ALeRCE, the detection and alert of supernova explosions (SNE), using prediction and distinguish between SNE, as well as other complex classes of events. Template classification is necessary for morphological differentiation of galactic nuclei, SNEs, stars, asteroids and false warnings. It uses rotational invariance of images. CNN is trained using entropy data and additional information that experts could use to evaluate candidates. Modern astronomical instruments are able to assess the level of chaos caused by the explosion of objects Reyes et al. (2018), estimate the size of a companion star Jiang et al. (2017), recognize, annotate and classify big data obtained from survey telescopes.

The article is structured as follows. First, the HIPPARCOS catalog is discussed, as well as an overview of the labor of the detection of binaries in this catalog. At the same time, the general principles of allocation of unresolved binary stars in the astrometric survey are discussed. Following this, a review of a calculation experiment using machine learning and ML methods in astronomical research is described. At the same time, considering the features of ML, significant and control signs of duality are distinguished, these signs are selected classifying singular and binary stars. The stability of the constructed classification to changes of the observational selection of the training sample is checked. In conclusion, an estimate of the proportion of binary stars to single stars in the catalog is given.
2. GROUND-BASED OBSERVATIONS AND CATALOGING OF BINARY STARS

The idea of the existence of physical binary and multiple star systems in the Universe was first considered by John Michell (1767). He applied then new statistical methods to the study of stars and demonstrated that many more stars occur in pairs or groups than a random distribution can explain. For the Pleiades cluster, Mitchell estimated that the probability of such a close group of stars is $5 \cdot 10^{-5}$. He concluded that stars in such binary or multiple star systems can attract each other, which is the first proof of the very fact of the existence of binary stars and star clusters. His work on binary stars may have influenced William Herschel’s research on the same topic, which took shape in the first catalog of binary stars Herschel (1785).

2.1. Modern astrometric, photometric, and spectral methods for determining the binarity of stars

Identifying objects with a small angular distance as binary stars was initially proposed (the so-called optical double stars, incredibly close to each other in the sky). Later it was supplemented by other methods, primary astrometric (see e.g. Makarov & Kaplan (2005)). Long-term observations of optical and astrometric binaries make it possible to determine the orbits of the components in some cases. Currently we are talking about hundreds of such objects Söderhjelm (1999); Hartkopf et al. (2001). This is the only direct method of determining the physical mass of stars.

Astrometric methods are good for investigating sufficiently wide star pairs. For closer components, which are unresolved, astrophysical methods (photometrical or spectroscopic) are more effective. In most cases, the duality of an object is revealed using criteria such as the Rayleigh criterion Arenou & Söderhjelm (2005); Griffin & Griffin (1986). Optical binary stars were discovered by applying Rayleigh criterion: if the distance between the components exceeds the half-width of the so-called point spread function (PSF), according to earlier methods, one considers the star to be optically binary. It is essential that for more than a hundred years the accuracy of determining the astrometric parameters of stars has been much better than PSF. This is related to the development of astrometric methods for detecting binary stars based on the features of their proper motions. Our work is also aimed at clarifying the criteria for detecting the duality of astrometric binary stars, which would be orders of magnitude more sensitive than the Rayleigh criterion.

2.2. Binary star catalogs, binarity in stellar surveys

Catalogs of binary stars have been published since the end of the XVIII century Herschel (1785). The development of the situation is shown in the table 1 for publications Burnham (1906); Aitken & Doolittle (1932); Jeffers et al. (1963); Lipaeva et al. (2014); Worley C.E. (1984); Worley & Douglass (1997); Mason et al. (2001, 2021); Dommanget & Nys (1994); Fabricius et al. (2002). It is easy to see that the growth of number of discovered binary systems is quite moderate: at the beginning of the XX century, astronomers used visual catalogs containing a total of about a million stars Schönfeld (1886); Gill & Kapteyn (1896, 1897, 1900); Argelander (1903), in the middle of the century, a photographic Carte du Ciel with about 4.5 million stars Eichhorn (1957); Sémirot (1972); Stock & Cova S. (1983) became available, the development of space astronomy required catalogs of tens of millions of objects Lasker et al. (1990); Russell et al. (1990); Jenkner et al. (1990); Morrison et al. (2001), and in the XXI century, electronic versions of photographic catalogs with a volume of about a billion stars were introduced to the scientific community Lasker et al. (2008); Monet et al. (2003). During this period, the volume of double star catalogs has grown only a few times.
Table 1. Catalogs of double stars

| ID    | Year | Total number of multiple systems | Total number of individual components | References                                                      |
|-------|------|----------------------------------|---------------------------------------|----------------------------------------------------------------|
| Herschel | 1785 | 434                              |                                       | Herschel (1785)                                                 |
| BDS    | 1906 | 13665                            |                                       | Burnham (1906)                                                 |
| ADS    | 1932 | 17180                            |                                       | Aitken & Doolittle (1932)                                      |
| IDS    | 1961 | 56572 (29965)                    | 69819 (36861)                         | Jeffers et al. (1963); Lipaeva et al. (2014)                   |
| WDS    | 1994 | 73610                            | 154333                                | Worley C.E. (1984); Worley & Douglass (1997); Mason et al. (2001, 2021) |
| CCDM   | 1994, 2002 | 34031                        | 74861                                 | Dommanget & Nys (1994)                                         |
| Tycho-3 | 2001 | 32631                            | 103259                                | Fabricius et al. (2002)                                        |

The above situation is typical for survey catalogs limited to the weakest observed stellar magnitude. Most of the stars in such a catalog Kharchenko (2001) are slightly brighter than the detection limit and identifying duality in this case is problematic.

A survey of the star catalogs, compiled according to a somewhat different principle: identification of all objects within a given volume of space Gliese & Jahreiß (1991), significantly changes the statistics Bastian et al. (2010); Duquennoy et al. (1991); Duquennoy & Mayor (1991). Dimmer objects of late spectral classes are beginning to prevail in the samples of the nearest to the Sun stars, and the proportion of stars with signs of duality is approaching 50%.

2.3. Theoretical models of the emergence of multiple stars, the percentage of binarity among the stars in the vicinity of the Solar System

There is no common opinion in the research of the modes of the collapse of protostellar clouds yet. For the appearance of single stars, theoretical models are well-regarded, and a sufficiently convincing initial mass function is obtained, which then gives reasonable results in further population calculations. So, according to Kroupa (2002), there are following equations for different masses of stars:

\[
\xi(M) = \begin{cases} 
  k_0 \left( \frac{M}{m_0} \right)^{-\alpha_0}, & m_0 < M \leq m_1 \\
  k_1 \left( \frac{M}{m_1} \right)^{-\alpha_1}, & m_1 < M \leq m_2 \\
  k_2 \left( \frac{M}{m_2} \right)^{-\alpha_2}, & m_2 < M 
\end{cases}
\]

where \(m_0 = 0.01 m_\odot, m_1 = 0.08 m_\odot, m_2 = 0.5 m_\odot, \alpha_0 = 0.3, \alpha_1 = 1.3, \alpha_2 = 2.3\). The last equation is the initial mass function of Salpeter (1955).

There is no generally accepted model of binary star formation yet. There are several theoretical models of the collapse of protostellar clouds with an initial rotation. In such models gas compression must lead to the formation of a toroidal structure. This structure then decays into separate protostars, which form a multiple star system (in the simplest case, a binary one). Taking into account various
physical mechanisms (for example, the degree of influence of the magnetic field) leads to significantly different results, none of which is fully confirmed by observations.

Our study of binary stars statistics is carried out under conditions Gliese & Jahreiß (1991) of extremely high probability of duality of objects (about 50%) and the absence of a generally accepted astrophysical theory.

3. HIPPARCOS MAIN CATALOG

The HIPPARCOS spacecraft became the first specialized astrometric satellite. High-precision optical measurements require a long-focus instrument, which therefore has a small field of view.

3.1. Observations technique and the structure of the catalog. Sources of information and data on binarity

The task of carrying out high-precision measurements throughout the entire celestial sphere determined the instrument design with two fields of view with a diameter of about 0.9° each, spaced from each other by ≈ 58°. The device rotated with a period of 120 minutes around an axis perpendicular to the plane in which the entrance pupils lie Perryman et al. (1989a), and the axis itself (according to the observation plan) slowly precessed along the cone of 43° around the direction to the Sun. All these movements combined led to a uniform coverage of the observations of the celestial sphere and, on the other hand, did not allow the satellite’s solar panels to deviate significantly from the direction of the Sun and lose power.

To increase the stability of the measurements, it wasn’t just the passage of a star in the field of view of an electric vacuum device that was being recorded, but its passage through a lattice of 2660 slits. The recorded coordinates thus ended up being one-dimensional, they were tied to a large circle, that remained the same for several revolutions of the satellite. During the processing stage, the parameters of the circles were linked to each other for the entire celestial sphere, then the spherical coordinates of individual stars, their parallaxes and proper motions were calculated Perryman et al. (1989b).

The results of the satellite observation ESA (1997) have shown the accuracy of coordinates better than of ground observations by about 100 times. During the experiment, this made it possible to determine the coordinates alongside parallaxes and proper motions with high accuracy of about 1 msec of arc. That is, an experiment of 3.5 years yielded a result comparable to the astrometric activity of an entire century and in some cases (in terms of high-precision parallaxes), even surpassing the results. We have to note that, strictly speaking, this is correct only of the objects of the HIPPARCOS program, with respect to a posteriori confirmation of the accepted source model.

The duality of objects in the HIPPARCOS main HIP catalog was initially established by their belonging to the Catalog of Components of Double and Multiple Stars (CCDM) Dommanget & Nys (1994). At the same time, new optical binaries reliably detected during the observations, separated by the Rayleigh-type criterion, were added to this catalog (about 5% of its volume).

3.2. Further work on the detection of double stars in HIP

After the publication of the main HIPPARCOS catalog and the additional Tycho catalog to the original program, their in-depth research began. The latest catalog was obtained based on observations not of the main HIPPARCOS spacecraft photodetector, but of the signals from service stellar sensors, initially intended to monitor the appearance of an object that is a part of the observation
program in the field of view immediately before the start of the main measurements. This additional material allows us to get the coordinates of about a million stars with an accuracy of an order of one to one and a half magnitude worse than in the main HIP catalog.

Considerable efforts of researchers were aimed at improving the accuracy of the Tycho catalog’s proper motions and increasing its size based on satellite observations records and the use of Carte du Ciel data, so Tycho-2 Høg et al. (2000) catalog appeared. Later on, this information formed an additional catalog of binary stars Tycho Fabricius et al. (2002) and the discovery of new binary stars in the main HIP catalog Makarov & Kaplan (2005). We will use the latter list below to test the operation of machine learning algorithms.

3.3. General principles of detection of unresolved binaries in an astrometric survey

It is apparent, that many different criteria for detecting the duality of an object by measuring any one parameter, such as the ellipsoid of the visible image, the deviation of proper motion from a straight line, anomalous photometry, bifurcation of spectral lines? have already been used, generally speaking, by the authors of observations or their closest followers and cannot yield anything new. The general principle of detecting duality in this case is approximately the same: the Rayleigh criterion in the latter case or the ellipticity of the image significant in comparison with the point spread function (PSF) in the first case, are similar to each other and do not make it possible to detect duality if the separation (or anomalous proper motion) of the components is less than the errors, the width of the spectral line or the same PSF.

On the other hand, it is obvious that the optical separation of the components of the assumed binary at distances greater than the errors of the coordinate measurements should somehow manifest itself in the results of the observations. Our work consists of verifying the fact that for unresolved, as well as for resolved, binary stars, anomalies in the errors of the measured values will appear.

The proposed method relies on using the widest possible set of data for each object. The next section shows how, based on a training sample, various artificial intelligence algorithms are trained, significant signs of duality and signs of negligible significance are highlighted. An additional check is also performed on the sampling effect, the influence of the chosen machine learning method, the influence of the observational selection in the training sample and the dependence on the imperfection of the reduction procedure of the main catalog. In addition, some of those parameters of stars that should not depend on duality are to be analyzed for the purpose to check the algorithms used.

4. APPLICATION OF ML METHODS FOR DETECTION OF BINARY STAR SYSTEMS

In this work we present the results of applying modern ML methods and AI systems to the data of HIP catalog to increase the quality of the data received via the astrometric satellite. More specifically, we used neural networks and decision tree-based models.

4.1. Feature extraction

The HIP catalog contains many characteristics of stars from the main list (there are 77 data fields in the catalog ESA (1997)). From them, we excluded fields like references to other catalogs or data sources. We also excluded astronomical coordinates, because on the one hand, the catalog covers only a small volume of the Galaxy in a close neighborhood of the Sun, where the structure of the Galaxy is not prominent. On the other hand, exact values of star coordinates are enough to uniquely identify a star, so the ML models will just remember which stars are binary and which are not, without trying to extract dependencies from other fields.
The spectral class field of a star is presented in the HIP Catalog as a text field, which prevents its direct use as an input to ML models. To use information from this field, the text format was converted to a synthetic (manually created) feature vector which describes the spectral data in a format, suitable for ML models. A complete set of features of this vector is shown in the Appendix A. Thus, the catalog data was mapped in a space of 73 features, including 34 numeric values taken directly from the HIP catalog and 39 features from the spectral classification fields. The table showing all catalog fields used in the analysis is shown in the Appendix B.

Non-empty value of CCDM field of HIP catalog was used as a target feature.

### 4.2. Data analysis models

In the AI research platform we have experimented with two kinds of models to process data: ensemble of neural networks and ensemble of XGBoost (eXtreme Gradient Boosting Chen & Guestrin (2016)) decision-tree trained models.

Neural network ensembles were built from feed-forward networks composing of two fully-connected hidden layers of 200 and 100 neurons with ReLU (Rectified Linear Unit) activation function, followed by an output layer of a single neuron with a sigmoid activation function. Before feeding data to the neural network, it was passed through a normalization layer. Networks was trained using Adam (Adaptive Moment Estimation) Kingma & Ba (2015) algorithm, optimizing for a binary cross-entropy metric. Neural networks were implemented and trained using Keras Chollet et al. (2015) library, included in Tensorflow deep learning framework Abadi et al. (2015).

To create an ensemble of neural networks, we split the original HIP catalog dataset into 25 random subsets, while preserving the proportion of target binarity feature in each subset. This was done using StratifiedShuffleSplit function from sklearn library Pedregosa et al. (2011). Then, each single subset was used as a training datum for a neural network, while the remaining 24 subsets where jointly used as a test set. Those 25 networks were grouped into an ensemble, which was used to calculate the final output value for all stars in the HIP Catalog.

An ensemble of decision-tree models was trained using the same technique. Base models were created using XGBClassifier implementation of the extreme gradient boosting algorithm from XGBoost library Chen & Guestrin (2016). The following parameters were used for each of 25 classifiers: learning_rate=0.01; n_estimators=1811; max_depth=6; min_child_weight=4; gamma=0.4; subsample=0.9; colsample_bytree=0.8; objective= 'binary:logistic'; nthread=4; scale_pos_weight=1; seed=27. Parameters, essential for learning were found using a cross-validation method.

Since there is reason to believe that not all multiple systems are marked in the HIPPARCOS catalog, we propose to use an approach that is often used in data analysis to identify labeling errors, to identify candidates for binary systems: train a classifier on an initial (incomplete in terms of labeling) data set and then consider objects with the maximum error as candidates for incorrect labeling Brodley & Friedl (1999); Zhu et al. (2003); Angelova et al. (2005); Huang et al. (2019).

In the context of our task this means that we are looking for stars, which are not marked as binary in HIPPARCOS catalog, but, at the same time, show a high probability of being binary based on the results of the ML models, trained on the datasets from the catalog. For such an object, it holds that, despite the fact that it was used in the training process as “not a binary star”, i.e. the ML model was instructed that the probability of its binarity equals 0, the ML algorithm, nevertheless, insists on its duality, based on the patterns it derives from the data.
4.3. Importance of features required for classifying a star as binary

XGBoost library provides means to access various statistics of a model, including feature importance’s for trained classifier. Fig. 1 shows that various statistical parameters from the catalog are significant, while, for example, the spectral parameters are not. It means that ML algorithms confirmed the well-known from the catalogs of double and multiple stars result, that duality of a star is only loosely correlated with the spectral characteristics of the pair. Thus, we can conclude that training dataset used is consistent in this regard.

![Feature Importances](image)

**Figure 1.** Features from the fields of HIPPARCOS catalog ranked by importance to produce the probability of duality of a star

Importance score shown on x-axis of Figure 2 represents the number of times the feature was used as a decision variable in trees, averaged over ensemble members. Our calculation experiments show that this feature is consistent across ensemble members and resilient to changes at random stages of algorithm training, like a split of the ensemble members into individual training groups, seed parameter of XGBClассifier.

4.4. Robustness of the classification algorithm

The training set for ML algorithms consists a subcategory of catalogs stars ESA (1997) assigned a non-empty value of CCDM Dommanget & Nys (1994) field, i.e. the star is recognized as a double. The very procedure for establishing binarity based on the anomalous proximity of neighboring stars (see above) is subject to a very strong observational selection: binarity according to catalogs Dommanget & Nys (1994); Mason et al. (2021) for bright stars (of which there are few) turns out to be much more probable than for more numerous faint stars. In order to test the influence of this effect on the work of ML algorithms, an independent training was carried out, during which photometric values from model input were excluded. The specific parameters that were used at this stage are given in the table in the Appendix B. The star color indices and photometric errors were retained as input parameters: the former — to control the adequacy of the classification algorithm, the latter — as one of the indicators of the possible duality of the object.

The results of the work of the HIPPARCOS consortium published in ESA (1997), included the solution of a system of nonlinear reduction equations for determining the kinematic parameters of
Adaptive algorithm for detecting double stars

Figure 2. The changes of probabilities of classifying a star as a singular or binary by different ML algorithms

stars. The system of equations was solved by the iteration method. One iteration in 1995-1996 took about half a year of calculations, and it was this iteration that was subsequently published. After 10 years, one of the members of the consortium repeated the processing of the observational material that had been preserved, somewhat improving the reduction scheme and achieving convergence of the iterations (at that time, one iteration took about a week of computing time). The resulting new HIPPARCOS reduction was published van Leeuwen (2007); van Leeuwen, Floor (2007) and showed slightly better accuracy, especially for bright stars. It has not been accepted as a coordinate standard, but is actively being used in scientific research.

To test the approach proposed in this paper, this new reduction is important, since it allows one to check the stability of ML algorithms to the non-Gaussian nature of the errors of the parameters being analyzed. Since the convergence of the solution of the system of nonlinear equations was not achieved in the HIP catalog (it was only possible to check the absence of noticeable divergence), the errors of the quantities being determined will inevitably have a non-zero mean, which indicates that they will be non-Gaussian.

The training of ML models was carried out using data from the original HIP catalog and data from its new reduction together. A specific list of fields taken from the new reduction van Leeuwen, Floor (2007) is given in the table in the Appendix C. Also, two Boolean fields were added, indicating the presence of a 7- and 9-component solution (the presence of a star in the hip7p.dat and hip9p.dat tables from van Leeuwen, Floor (2007)). The specific values of these solutions were not used, since they are available only for a small part of the catalog stars, and it is unlikely that they will be effectively used by the ML models in this regard.

The experiment with machine learning based on the material van Leeuwen, Floor (2007) showed stability of the values of the main statistical characteristics in the catalog for the purpose of classifying objects as binary stars (Fig. 2). The resilience of the results to the sampling effect was also tested.

4.5. Prediction of duality probability of HIP catalog stars by ML models

Since the output of the proposed models is the probability of duality for each of the stars of the HIPPARCOS catalog, it is natural to consider stars, for which probability exceeds a certain threshold as candidates for binary stars. Figure 3 shows how many new candidates for binary systems can be
Figure 3. Number of candidates to double systems as a function of threshold on model probability

identified using the proposed models for different threshold values. The solid lines correspond to binary system candidates identified in comparison with the labeling of the original HIP catalog, and the dotted lines correspond to those found in work Makarov & Kaplan (2005). The graph at the bottom of the figure shows what the percentage of multiple systems in the catalog will be at different values of the probability threshold.

As outputs of two models — ensemble of neural networks and ensemble of decision trees differ from each other, it is a natural next step to group these models together into one joint ensemble including models of both types. In Fig. 3, along with the results of the ensemble of neural networks and the ensemble of decision trees, the results of the combined model are also presented.

The data in Fig. 3 correspond to the results obtained when training models using the data from both the original HIP catalog Perryman et al. (1997) and the new reduction van Leeuwen, Floor (2007), using a set of variables that limits the effect of observational selection. The methodology used in this work does not imply the identification of all binary star candidates in one run. Solving the problem of data analysis under conditions of partially incorrect labeling Brodley & Friedl (1999); Zhu et al. (2003); Angelova et al. (2005); Huang et al. (2019) implies an iterative process, during which after identifying the most probable labeling errors (in our case, previously unidentified double stars), it is necessary to check the corresponding objects, correct the labeling and repeat training.
This cycle can be repeated several times until a satisfactory result is achieved. This article presents the first iteration of this process.

4.6. Comparison of ML methods’ results with other publications

The comparison was carried out on the most extensive work on the identification of additional double stars in the HIP catalog — the paper by Makarov and Kaplan Makarov & Kaplan (2005), where the astrometric method was used, with additional information from the Tycho-2 catalog Høg et al. (2000).

![Figure 4. Comparison of ML algorithms’ results with Makarov and Kaplan](image)

Figure 4. Comparison of ML algorithms’ results with Makarov and Kaplan

Figure 4A shows the probabilities computed by our ML models for stars identified as double in Makarov & Kaplan (2005). The axes of the graph correspond to probabilities of duality calculated by the ensemble of neural networks and the ensemble of tree classifiers.

In Figure 4B there are also stars that are not designated as double either in Makarov & Kaplan (2005) or in the original HIPPARCOS catalog along with the stars identified in Makarov & Kaplan (2005), with a binarity probability estimates of > 60% from the ML models.

Analyzing graph 4(A), one can see that most of the multiple stars identified in Makarov & Kaplan (2005) received low probabilities of duality when assessed using the ML system. On the other hand, plot 4(B) shows that most of the stars proposed as candidates for duality by the ML models were not identified in Makarov & Kaplan (2005). Thus, we can conclude that the patterns identified by machine learning models and the corresponding candidate stars differ from the results of Makarov & Kaplan (2005).

In this regard, it may be of interest to include the binary stars identified in Makarov & Kaplan (2005) in the training set, to train and study the resulting models.

4.7. Observation-based model verification

To verify the obtained results of applying ML to the objects of the HIPPARCOS catalog, the lists of the most probable double stars were compared to the double stars from the Pan-STARRS catalog of objects Chambers & et al. (2017). The search for neighbors was carried out in the vicinity of the
Table 2. Identification of double star candidates in PS1

| selection criteria | number of objects | multiplicity found (components found) | components not found | star not found |
|--------------------|-------------------|---------------------------------------|----------------------|---------------|
| NN, $p > 0.8$      | 214               | 142 (895*)                            | 10$^b$               | 72            |
| XGB, $p > 0.7$     | 109               | 69 (430*)                             | 5$^c$                | 50            |

$^a$ the catalog PS1 was obtained from the observations of the telescope installed in the Hawaiian Islands, part of the sky is not available for observation

$^b$ 2 spectroscopic binaries, 3 stars with large proper motion, 1 against the background of the galaxy

$^c$ 3 spectroscopic binaries

HIPPARCOS star with a radius of 5″. This is the size of the working area of the photodetector that took the measurements.

Thus, the developed mechanism gives a 90-95% probability of correct prediction of duality (recall that a priori the probability of duality of a randomly selected star is about 50%).

5. CONCLUSIONS

The methodological approach developed in the Cognotron research platform and presented in the article and the experiments performed show that the use of machine learning methods on the data of the HIPPARCOS catalog makes it possible to extract additional information and identify double and multiple star systems that could not be previously detected by classical methods. This is the result of a discovery of complex relationships between astrometric and photometric characteristics and the errors of these characteristics by machine learning methods. Classical methods are based on an analysis of isolated characteristics, or small groups of characteristics, and are limited by the accuracy of their measurements. The combination of a larger number of characteristics and their errors in the analysis, which is achieved by using machine learning methods, is equivalent to using a larger number of accumulated light quanta during long-term observation, which makes it possible to increase the accuracy of detecting binary stars.

The disadvantage of the proposed method is that it does not allow introducing a strict criterion for the duality of stars. In classical methods, criteria of this kind are formulated on the basis of known physical laws prior to the analysis. However, it is not theoretically possible to formulate such a criterion that would describe the relationship between several dozen characteristics. Machine learning methods in this case rely on an automated extraction of dependencies from labeled data. But, in the case in picture, there is no correctly labeled training sample, and any patterns are extracted from data in which a significant part of binary stars are not labeled as such.

An immediate consequence of this situation is that the output values of the data analysis models proposed in this paper cannot be considered as probabilities of stellar duality. Since the proportion of binary stars in the training sample is underestimated, it should be expected that the output values will also be underestimated compared to the true probabilities.

The procedure for detecting binary stars is also becoming more complicated. To fully use the potential of the method proposed in this paper, it is necessary to implement an iterative procedure, during which the binary star candidates proposed by the ML models will need to be independently
verified; the labeling of the training data will change based on this verification, new models will be trained that will offer the next set of candidates and so on.

This article, in fact, presents the results of one such iteration. It is important that this work demonstrates that during such iteration, it is indeed possible to select objects with a high probability of duality (90% of the objects were confirmed according to the PS1 catalog). It means that:

- in the HIPPARCOS data, there are indeed significant dependencies indicating the duality of stellar systems;
- existing machine learning methods allow such dependencies to be detected and used to identify dual stars that were not detected by classical methods.

Significant features identified by ML algorithms for the dual star classification are of high interest as well. In the process of training and verifying ML models, it turned out that machine learning algorithms quite reliably identify a group of significant features associated with the statistical characteristics of the observed values. It is also shown that the identification of duality only loosely depends on the spectral characteristics of the pair. The methods turned out to be resilient to observational selection in the training set itself. In addition, the parameters of objects in the HIPPARCOS catalog, which, according to the studies of other authors, are not related to the multiplicity/duality of stars (for example, various spectral characteristics), showed low significance, which was additional evidence of the effectiveness of this method.

The application of the digital ML methods-based approach proposed in this paper to data and catalogs of other missions (for example, GAIA, van Leeuwen et al. (2021)) is also possible and promising, but so far seems premature. Combining data across multiple missions is of theoretical interest, but may be accompanied by difficulties due to the difference in the values obtained by different instruments and due to different observation schemes. In addition, their statistical characteristics will also differ, which may introduce difficulties for ML algorithms. An additional complication arises from the difference in the operating ranges of stellar magnitudes, although an intersection does take place. Such a combination is also complicated by the fact that, according to pre-flight plans, the publication of data on relatively complex objects will be carried out at the final stages of the experiment.

Despite the difficulties and obstacles that arise, the ML approach proposed in this paper is more accurate in its measurements and can help extract new knowledge and stimulate the generation of new ideas, compared to the classical approach. A specific AI platform named “Cognotron” was used in our study.
### Table 3. Spectrum Description fields

| Field               | Range | Description                                      | Notation in the field SpType |
|---------------------|-------|--------------------------------------------------|------------------------------|
| SpectralClass       | 0...8 | Spectral class                                   | O, B, A, F, G, K, M, L, T, C, S, SC, WN, WC, WO, WR, R, N, DA, DB, DC, DO, DZ, DQ, DG, DF, CN |
| Luminosity_I        | Boolean | Luminosity Class I                              | I, Ia, Iab, Ib               |
| Luminosity_II       | Boolean | Luminosity Class II                             | II, IIa, IIb                 |
| Luminosity_III      | Boolean | Luminosity Class III                            | III, IIIa, IIIb              |
| Luminosity_IV       | Boolean | Luminosity Class IV                             | IV, IVa                      |
| Luminosity_V        | Boolean | Luminosity Class V                              | V, Va, Vb                    |
| Luminosity_VI       | Boolean | Luminosity Class VI                             | VI                           |
| Luminosity_uncertain | Boolean | Luminosity class is not precisely defined      | :                            |
| subdwarf            | Boolean | Subdwarf                                        | sd                           |
| WhiteDwarf          | Boolean | White dwarf                                      | DA, DB, DC, DO, DZ, DQ, DG, DF |
| W                   | Boolean | Wolf-Rayet star                                  | WN                           |
| Carbon              | Boolean | C-type star (Carbon star)                        | C                            |
| S                   | Boolean | S-type star (Zirconium star)                     | SC                           |
| R                   | Boolean | Spectral class R                                 | R                            |
| N                   | Boolean | Spectral class N                                 | N                            |
| MN                  | Boolean |                                               | MN                           |
| nebuluous           | 0, 1, 2 | Wide spectrum lines                             | n, nn, n:                    |
| enhanced_metal      | Boolean | Strong Metal Lines                               | m, m:                        |
| peculiar            | Boolean | Spectrum Peculiarities                           | p, p:, +pec                  |
| shell               | Boolean | Shell Star                                       | sh, +shell, shell            |
| emission            | Boolean | Emission lines                                   | e, e:, eq:, E                |
| weak_lines          | Boolean | Weak lines                                       | w, wk, wl                    |
| sharp_lines         | Boolean | Narrow lines                                     | s, ss, s:                    |

*Table 3 continued on next page*
### Table 3 (continued)

| Field               | Range     | Description                                                                 | Notation in the field SpType |
|---------------------|-----------|-----------------------------------------------------------------------------|------------------------------|
| variable            | Boolean   | Variable spectr                                                             | v, va, var                   |
| weak_helium         | Boolean   | Weak lines of Helium                                                        | Hewk                         |
| NIIandHeIIEmission  | Boolean   | N III emission, absence or weak absorption of He II                         | (f)                          |
| HeIIabsorbtionNIIemission | Boolean | strong He II absorption, weak N III emission                                 | ((f))                        |
| composite           | Boolean   | A spectrally double star                                                    | comp                         |
| undescribed_peculiarities | Boolean | Other features                                                              | "", ..., +,..., +,..., +...   |
| SB                  | Boolean   | Spectroscopic binary                                                        | SB, SB1, SB:                 |
| Sr                  | Boolean   | Spectral lines of Strontium                                                  | Sr, Sr:                      |
| Cr                  | Boolean   | Spectral lines of Chromium                                                  | Cr                           |
| Eu                  | Boolean   | Spectral lines of Europium                                                   | Eu                           |
| Mn                  | Boolean   | Spectral lines of Manganese                                                  | Mn                           |
| Hg                  | Boolean   | Spectral lines of Mercury                                                   | Hg, Hg:                      |
| Si                  | Boolean   | Silicon spectral lines                                                      | Si                           |
| Li                  | Boolean   | Lithium spectral lines                                                      | Li                           |
| Del                 | Boolean   | Spectrum like Delta Delphini                                                 | delDel, dDel, deltaDel        |
| Nova                | Boolean   | Nova Star                                                                   | Nova                         |
Table 4. Used parameters from the HIPPARCOS catalog

| Name     | Description in the HIPPARCOS catalog      | Used in the full set | Used in a set with a restriction of observational selection |
|----------|-------------------------------------------|----------------------|-------------------------------------------------------------|
| (1)      | (2)                                       | (3)                  | (4)                                                         |
| Name     |                                           |                      |                                                             |
| Catalog  | Catalogue (H=Hipparcos)                   |                      |                                                             |
| HIP      | Identifier (HIP number)                   |                      |                                                             |
| Proxy    | Proximity flag                            |                      |                                                             |
| RAhms    | Right ascension in h m s, ICRS (J1991.25)  |                      |                                                             |
| DEdms    | Declination in deg ', ', ICRS (J1991.25)   |                      |                                                             |
| Vmag     | Magnitude in Johnson V                     | +                    |                                                             |
| VarFlag  | Coarse variability flag                   | +                    | +                                                           |
| r_Vmag   | Source of magnitude                       |                      |                                                             |
| RAdeg    | alpha, degrees (ICRS, Epoch=J1991.25)      |                      |                                                             |
| DEdeg    | delta, degrees (ICRS, Epoch=J1991.25)      |                      |                                                             |
| AstroRef | Reference flag for astrometry             |                      |                                                             |
| Plx      | Trigonometric parallax                    | +                    | +                                                           |
| pmRA     | Proper motion mu_alpha*cos(delta), ICRS    | +                    | +                                                           |
| pmDE     | Proper motion mu_delta, ICRS               | +                    | +                                                           |
| e_RAdeg  | Standard error in RA*cos(Dedeg)            | +                    |                                                             |
| e_DEdeg  | Standard error in DE                       | +                    |                                                             |
| e_Plx    | Standard error in Plx                      | +                    | +                                                           |
| e_pmRA   | Standard error in pmRA                    | +                    | +                                                           |
| e_pmDE   | Standard error in pmDE                    | +                    | +                                                           |
| DE_RA    | Correlation, DE/RA*cos(delta)              | +                    | +                                                           |
| Plx_RA   | Correlation, Plx/RA*cos(delta)             | +                    | +                                                           |
| Plx_DE   | Correlation, Plx/DE                        | +                    | +                                                           |
| pmRA_RA  | Correlation, pmRA/RA*cos(delta)            | +                    | +                                                           |
| pmRA_DE  | Correlation, pmRA/DE                       | +                    | +                                                           |
| pmRA_Plx | Correlation, pmRA/Plx                      | +                    | +                                                           |
| pmDE_RA  | Correlation, pmDE/RA*cos(delta)            | +                    | +                                                           |
| pmDE_DE  | Correlation, pmDE/DE                       | +                    | +                                                           |
| pmDE_Plx | Correlation, pmDE/Plx                      | +                    | +                                                           |
| pmDE_pmRA| Correlation, pmDE/pmRA                     | +                    | +                                                           |

Table 4 continued on next page
### Table 4 (continued)

| Name | Description in the HIPPARCOS catalog | Used in the full set | Used in a set with a restriction of observational selection |
|------|--------------------------------------|----------------------|-------------------------------------------------------------|
| (1)  | (2)                                  | (3)                  | (4)                                                          |
| F1   | Percentage of rejected data          | +                    | +                                                            |
| F2   | Goodness-of-fit parameter            | +                    | +                                                            |
| H31  | HIP number (repetition)              |                      |                                                              |
| BTmag| Mean BT magnitude                    | +                    |                                                              |
| e_BTmag| Standard error on BTmag              | +                    |                                                              |
| VTmag| Mean VT magnitude                    | +                    |                                                              |
| e_VTmag| Standard error on VTmag              | +                    |                                                              |
| m_BTmag| Reference flag for BT and VTmag     |                      |                                                              |
| B_V  | Johnson B-V colour                   | +                    | +                                                            |
| e_B_V| Standard error on B-V                | +                    | +                                                            |
| r_B_V| Source of B-V from Ground or Tycho   |                      |                                                              |
| V_I  | Colour index in Cousins’ system      | +                    | +                                                            |
| e_V_I| Standard error on V-I                | +                    | +                                                            |
| r_V_I| Source of V-I                        |                      |                                                              |
| CombMag| Flag for combined Vmag, B-V, V-I    |                      |                                                              |
| Hpmag| Median magnitude in Hipparcos system | +                    |                                                              |
| e_Hpmag| Standard error on Hpmag              | +                    | +                                                            |
| Hpscat| Scatter on Hpmag                     | +                    | +                                                            |
| o_Hpmag| Number of observations for Hpmag    |                      |                                                              |
| m_Hpmag| Reference flag for Hpmag            |                      |                                                              |
| Hpmax| Hpmag at maximum (5th percentile)   |                      |                                                              |
| HPmin| Hpmag at minimum (95th percentile)  |                      |                                                              |
| Period| Variability period (days)            | +                    | +                                                            |
| HvarType| Variability type                   |                      |                                                              |
| moreVar| Additional data about variability   |                      |                                                              |
| morePhoto| Light curve Annex                   |                      |                                                              |
| CCDM | CCDM identifier                     |                      |                                                              |
| n_CCDM| Historical status flag              |                      |                                                              |
| Nsys | Number of entries with same CCDM    |                      |                                                              |
| Ncomp| Number of components in this entry   |                      |                                                              |
| MultFlag| Double/Multiple Systems flag        |                      |                                                              |
| Source| Astrometric source flag             |                      |                                                              |
| Qual | Solution quality                    |                      |                                                              |
| m_HIP| Component identifiers               |                      |                                                              |

*Table 4 continued on next page*
Table 4 (*continued*)

| Name          | Description in the HIPPARCOS catalog | Used in the full set | Used in a set with a restriction of observational selection |
|---------------|--------------------------------------|----------------------|----------------------------------------------------------|
| theta         | Position angle between components    |                      |                                                          |
| rho           | Angular separation between components|                      |                                                          |
| e_rho         | Standard error on rho                |                      |                                                          |
| dHp           | Magnitude difference of components   |                      |                                                          |
| e_dHp         | Standard error on dHp                |                      |                                                          |
| Survey        | Flag indicating a Survey Star        |                      |                                                          |
| Chart         | Identification Chart                 |                      |                                                          |
| Notes         | Existence of notes                   |                      |                                                          |
| HD            | HD number <III/135>                  |                      |                                                          |
| BD            | Bonner DM <I/119>, <I/122>           |                      |                                                          |
| CoD           | Cordoba Durchmusterung (DM) <I/114>  |                      |                                                          |
| CPD           | Cape Photographic DM <I/108>         |                      |                                                          |
| V_I_red       | V-I used for reductions              |                      |                                                          |
| SpType        | Spectral type \(^2\)                | +                    | +                                                        |
| r_SpType      | Source of spectral type              |                      |                                                          |

\(^2\) the list of used fields in decoded form is given in the Appendix A
### Table 5. Used parameters from the paper of Floor van Leeuwen

| Name          | Description from the paper of Floor van Leeuwen | Used in the full set | Used in a set with a restriction of observational selection |
|---------------|--------------------------------------------------|----------------------|-------------------------------------------------------------|
| HIP           | Hipparcos identifier                             |                      |                                                             |
| Sn            | Solution type new reduction                      |                      |                                                             |
| So            | Solution type old reduction                      |                      |                                                             |
| Nc            | Number of components                             | +                    |                                                             |
| RA_rad        | Right Ascension in ICRS, Ep=1991.25              |                      |                                                             |
| DE_rad        | Declination in ICRS, Ep=1991.25                  |                      |                                                             |
| Plx           | Parallax                                         | +                    |                                                             |
| pm_RA         | Proper motion in Right Ascension                 | +                    |                                                             |
| pm_DE         | Proper motion in Declination                     | +                    |                                                             |
| e_RA_rad      | Formal error on RA_rad                           | +                    | +                                                           |
| e_DE_rad      | Formal error on DE_rad                           | +                    | +                                                           |
| e_plx         | Formal error on Plx                              | +                    | +                                                           |
| e_pm_RA       | Formal error on pm_RA                            | +                    | +                                                           |
| e_pm_DE       | Formal error on pm_DE                            | +                    | +                                                           |
| N_tr          | Number of field transits used                    | +                    |                                                             |
| F2            | Goodness of fit                                  | +                    | +                                                           |
| F1            | Percentage rejected data                         | +                    | +                                                           |
| var           | Cosmic dispersion added                          |                      |                                                             |
| ic            | Entry in one of the suppl.catalogues             |                      |                                                             |
| H_pmag        | Hipparcos magnitude                              | +                    |                                                             |
| e_H_pmag      | Error on mean H_pmag                             | +                    | +                                                           |
| sHp           | Scatter of H_pmag                                | +                    | +                                                           |
| VA            | [0.2] Reference to variability annex             |                      |                                                             |
| B-V           | Colour index                                     | +                    |                                                             |
| e_B-V         | Formal error on colour index                     | +                    | +                                                           |
| V-I           | V-I colour index                                 | +                    |                                                             |
| UW            | Upper-triangular weight matrix<sup>4</sup>       | +                    | +                                                           |

<sup>4</sup> each element of the matrix is represented as a separate parameter
REFERENCES

Abadi, M., Agarwal, A., Barham, P., et al. 2015, TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems. https://www.tensorflow.org/

Aitken, R. G., & Doolittle, E. 1932, New General Catalogue of Double Stars within 120° of the North Pole (Washington, D.C.: Carnegie institution of Washington).

ALeRCE. 2022, Automatic Learning for the Rapid Classification of Events. http://alerce.science/

Angelova, A., Abu-Mostafa, Y. S., & Perona, P. 2005, in 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR 2005), 20-26 June 2005, San Diego, CA, USA (IEEE Computer Society), 494–501, doi: 10.1109/CVPR.2005.283

Arenou, F., & Söderhjelm, S. 2005, in ESA Special Publication, Vol. 576, The Three-Dimensional Universe with Gaia, ed. C. Turon, K. S. O’Flaherty, & M. A. C. Perryman, 557

Argelander, F. W. A. 1903, Eds Marcus and Weber’s Verlag, 0

Bastian, N., Covey, K. R., & Meyer, M. R. 2010, ARA&A, 48, 339, doi: 10.1146/annurev-astro-082708-101642

Becker, I., Pichara, K., Catelan, M., et al. 2020, MNRAS, 493, 2981, doi: 10.1093/mnras/staa350

Broder, C. E., & Friedl, M. A. 1999, Journal of Artificial Intelligence Research (JAIR), 11, 131, doi: 10.1613/jair.606

Burnham, S. W. 1906, A General Catalogue of Double Stars within 121° of the North Pole (Carnegie institution of Washington; [Chicago, University of Chicago press])

Carrasco-Davis, R., Reyes, E., Valenzuela, C., et al. 2021, AJ, 162, 231, doi: 10.3847/1538-3881/ac0ef1

Chambers, K. C., & et al. 2017, VizieR Online Data Catalog, II/349

Chen, T., & Guestrin, C. 2016, in Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD ’16 (New York, NY, USA: Association for Computing Machinery), 785–794, doi: 10.1145/2939672.2939785

Chollet, F., et al. 2015, Keras, https://keras.io

Dommanget, J., & Nys, O. 1994, Communications de l’Observatoire Royal de Belgique, 115, 1

Duquennoy, A., & Mayor, M. 1991, A&A, 500, 337

Duquennoy, A., Mayor, M., & Halbwachs, J. L. 1991, A&AS, 88, 281

Eichhorn, H. K. 1957, AJ, 62, 142, doi: 10.1086/107493

ESA. 1997, ESA Special Publication, Vol. 1200, The HIPPARCOS and TYCHO catalogues. Astrometric and photometric star catalogues derived from the ESA HIPPARCOS Space Astrometry Mission (ESA)

Fabricius, C., Hög, E., Makarov, V. V., et al. 2002, A&A, 384, 180, doi: 10.1051/0004-6361:20011822

Gill, D., & Kapteyn, J. C. 1896, Annals of the Cape Observatory, 3, 1

—. 1897, Annals of the Cape Observatory, 4, 1

—. 1900, Annals of the Cape Observatory, 5, 1

Gliese, W., & Jahreiß, H. 1991, Preliminary Version of the Third Catalogue of Nearby Stars: On the Astronomical Data Center CD-ROM; Selected Astronomical Catalogs

Griffin, R., & Griffin, R. 1986, Journal of Astrophysics and Astronomy, 7, 195, doi: 10.1007/BF02714210

Hartkopf, W. I., Mason, B. D., & Worley, C. E. 2001, AJ, 122, 3472, doi: 10.1086/323921

Herschel, W. 1785, Philosophical Transactions of the Royal Society of London, 75, 40. http://www.jstor.org/stable/106749

Hilditch, R. W. 2001, An Introduction to Close Binary Stars (Cambridge University Press), doi: 10.1017/CBO9781139163576

Hög, E., Fabricius, C., Makarov, V. V., et al. 2000, A&A, 355, L27

Huang, J., Qu, L., Jia, R., & Zhao, B. 2019, in Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)

Jeffers, H. M., van den Bos, W. H., & Greeley, F. M. 1963, Index Catalogue of Visual Double Stars, 1961.0 (Publications of the Lick Observatory, Mount Hamilton: University of California, Lick Observatory), part 1 (263pp) + part part 2 (804pp)
Adaptive algorithm for detecting double stars

Jenkner, H., Lasker, B. M., Sturch, C. R., et al. 1990, AJ, 99, 2082, doi: 10.1086/115485
Jiang, J., Doi, M., ichi Maeda, K., et al. 2017, Nature, 550, 80
Kharchenko, N. V. 2001, Kinematika i Fizika Nebesnykh Tel, 17, 409
Kingma, D. P., & Ba, J. 2015, in 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings, ed. Y. Bengio & Y. LeCun. http://arxiv.org/abs/1412.6980
Kroupa, P. 2002, Science, 295, 82, doi: 10.1126/science.1067524
Lasker, B. M., Sturch, C. R., McLean, B. J., et al. 1990, AJ, 99, 2019, doi: 10.1086/115483
Lasker, B. M., Lattanzi, M. G., McLean, B. J., et al. 2008, AJ, 136, 735, doi: 10.1088/0004-6256/136/2/735
Lipaeva, N. A., Sementsov, V. N., & Malkov, O. Y. 2014, Baltic Astronomy, 23, 245, doi: 10.1515/astro-2017-0186
Makarov, V. V., & Kaplan, G. H. 2005, AJ, 129, 2420, doi: 10.1086/429590
Mason, B. D., Wycoff, G. L., Hartkopf, W. I., Douglass, G. G., & Worley, C. E. 2001, AJ, 122, 3466, doi: 10.1086/323920
—. 2021, The Washington Visual Double Star Catalog: B/wds, http://vizier.u-strasbg.fr/viz-bin/VizieR?-source=B/wds
Michell, J. 1767, Philosophical Transactions of the Royal Society of London Series I, 57, 234
Monet, D. G., Levine, S. E., Canzian, B., et al. 2003, AJ, 125, 984, doi: 10.1086/345888
Morrison, J. E., Röser, S., McLean, B., Bucciarelli, B., & Lasker, B. 2001, AJ, 121, 1752, doi: 10.1086/313983
Pedregosa, F., Varoquaux, G., Gramfort, A., et al. 2011, Journal of Machine Learning Research, 12, 2825.
http://jmlr.org/papers/v12/pedregosa11a.html
Perryman, M. A. C., Hassan, H., Batut, T., & et al. 1989a, The Hipparcos mission. Pre-launch status. Volume I: The Hipparcos satellite.
Perryman, M. A. C., Lindegren, L., Murray, C. A., & et al. 1989b, The Hipparcos mission. Pre-launch status. Volume III: The data reductions.
Perryman, M. A. C., Turon, C., Arenou, F., & et al. 1989c, The Hipparcos mission. Pre-launch status. Volume II: The Input Catalogue.
Perryman, M. A. C., Lindegren, L., Kovalevsky, J., et al. 1997, A&A, 500, 501
Raikov, A. 2021, Cognitive Semantics of Artificial Intelligence: A New Perspective, SpringerBriefs in Applied Sciences and Technology edn. (Springer Singapore), doi: 10.1007/978-981-33-6750-0
Reyes, E., Estévez, P. A., Reyes, I., et al. 2018, 2018 International Joint Conference on Neural Networks (IJCNN), 1
Russell, J. L., Lasker, B. M., McLean, B. J., Sturch, C. R., & Jenkner, H. 1990, AJ, 99, 2059, doi: 10.1086/115484
Salpeter, E. E. 1955, ApJ, 121, 161, doi: 10.1086/145971
Schönfeld, E. 1886, Eds Marcus and Weber’s Verlag, 0
Sémiot, P. 1972, Vistas in Astronomy, 13, 153, doi: 10.1016/0083-6656(72)90008-6
Söderhjelm, S. 1999, A&A, 341, 121
Stock, J., & Cova S., J. 1983, RMxAA, 5, 233
van Leeuwen, F. 2007, A&A, 474, 653, doi: 10.1051/0004-6361:20078357
van Leeuwen, F., de Bruijne, J., Babusiaux, C., et al. 2021, GAIA EDR3 documentation, https://ui.adsabs.harvard.edu/abs/2021gdr3.reptE....V
van Leeuwen, Floor. 2007, Astrophysics and Space Science Library, Vol. 350, Hipparcos, the New Reduction of the Raw Data (Springer), doi: 10.1007/978-1-4020-6342-8
Wang, P., Li, X., & Hammer, P. 2018, Frontiers in Robotics and AI, 5, doi: 10.3389/frobt.2018.00020
Worley, C. E., & Douglass, G. G. 1997, A&AS, 125, 523, doi: 10.1051/aas:1997239
Worley C.E., D. G. 1984, The Washington Double Star Catalog, US Naval Obs., unpublished
Zhu, X., Wu, X., & Chen, Q. 2003, in Machine Learning, Proceedings of the Twentieth International Conference (ICML 2003), August 21-24, 2003, Washington, DC, USA, ed. T. Fawcett & N. Mishra (AAAI Press), 920–927. http://www.aaai.org/Library/ICML/2003/icml03-119.php