Unary and Binary Classification Approaches and their Implications for Authorship Verification

Oren Halvani, Christian Winter, Lukas Graner

Abstract

Retrieving indexed documents, not by their topical content but their writing style opens the door for a number of applications in information retrieval (IR). One application is to retrieve textual content of a certain author X, where the queried IR system is provided beforehand with a set of reference texts of X. Authorship verification (AV), which is a research subject in the field of digital text forensics, is suitable for this purpose. The task of AV is to determine if two documents (i.e., an indexed and a reference document) have been written by the same author X. Even though AV represents a unary classification problem, a number of existing approaches consider it as a binary classification task. However, the underlying classification model of an AV method has a number of serious implications regarding its prerequisites, evaluability, and applicability. In our comprehensive literature review, we observed several misunderstandings regarding the differentiation of unary and binary AV approaches that require consideration. The objective of this paper is, therefore, to clarify these by proposing clear criteria and new properties that aim to improve the characterization of existing and future AV approaches. Given both, we investigate the applicability of eleven existing unary and binary AV methods as well as four generic unary classification algorithms on two self-compiled corpora. Furthermore, we highlight an important issue concerning the evaluation of AV methods based on fixed decision criterions, which has not been paid attention in previous AV studies.

1 Introduction

Document classification plays a vital role across numerous fields of studies including library, information or computer science and represents a major task in IR. The categorization of documents can be performed regarding a variety of concepts such as genre, register, text type, domain, sublanguage or style. Focusing on the (writing) style of documents allows a number of promising applications in IR. For example, a user can provide an IR system reference texts of an author A such as blog posts and ask the system to retrieve additional content of A (e.g., product reviews, articles or comments) based on the same writing style. Style-based IR is in particular interesting if both reference and indexed documents stem from the same person but differ in terms of meta data (for instance, different user names) or are not even provided with meta data at all. This might be a helpful supplement in the context of fake news detection.

A number of research disciplines exist that concern themselves with the analysis of writing style (more precisely, with the authorship of documents), where the most important are authorship attribution (AA) and authorship verification (AV). The former deals with the problem to identify the most likely author of an unknown document $D_U$, given a set of texts of candidate authors. AV, on the other hand, focuses on the question if $D_U$ was in fact written by a known author $A$, where only a set $D_A$ of reference texts of this author is given. Both disciplines are strongly related to each other, as any AA problem can be broken down into a series of AV problems [35]. Here, an AV system must determine for each verification problem $\rho = (D_U, D_A)$, if all involved documents stem from the same author, based on a specific decision criterion. Breaking down an AA problem into multiple AV problems is especially important in such scenarios, where the presence of $D_U$’s true author in the candidate set cannot be guaranteed. In contrast to AA, which represents an n-ary (multi-class) classification problem, AV is a unary (one-class) classification problem, as

\[\text{Note that “documents” are not necessarily restricted to natural language, but might also represent source code snippets or other types of textual data.}\]

\[\text{There are also other formulations that describe authorship verification problems (see, for example, [42]).}\]

\[\text{In this form, as highlighted in [17], AV is considered to be a recognition rather than a classification problem.}\]
there is only one class (A) to learn from [17, 26, 34, 36, 42]. However, inspecting previous studies reveals that unary classification appears to be a gray area in machine learning and, in particular, in the context of AV, where a number of misunderstandings can be observed.

The objective of this paper is to analyze these misunderstandings in detail and to propose clear criteria and properties that aim to close the gap of existing definitions and attempts to characterize AV methods, especially regarding the underlying classification models. By this, we hope to contribute to the further development of this young research field. Based on our definitions, we investigate the applicability of eleven existing unary and binary AV methods as well as four generic unary classification algorithms on two self-compiled corpora, which we make available for the AV community. Furthermore, we elaborate the implications that have to be faced for each approach and highlight an important issue concerning the evaluation of such AV methods that are based on fixed decision criterions.

2 Existing Approaches

In order to design an AV method, a wide spectrum of possibilities exists including unary, binary and n-ary classification approaches. In the following subsection, we first describe a number of generic unary classification algorithms that can and have been used in the context of AV. Afterwards, we present existing AV approaches that were partially motivated by these algorithms. All introduced approaches will be assessed regarding their performance in Sec. 4, where each approach will be categorized according to our proposed criteria and properties.

2.1 Generic Unary Classification Algorithms

As can be observed in the literature (for example, [10, 11, 19, 32]), a number of existing AV methods are based on unary classification algorithms. In the following, we therefore provide a brief overview of some selected approaches, which were also considered in our evaluation.

2.1.1 One-Class Nearest Neighbor

One very simple, but quite effective, unary classification algorithm is OCNN (One-class Nearest Neighbor [43]). Given a unknown document $D_U$, the known documents $D_A = \{D_1, D_2, \ldots, D_n\}$ and a predefined distance function, the idea behind OCNN is that $D_U$ is accepted as a member of the target class $A$, if its closest neighbor $D_i$ within $D_A$ is closer to $D_U$ than the closest neighbor of $D_i$ within $D_A \backslash \{D_i\}$. A number of existing AV approaches including [10, 11, 20] represent modifications of OCNN.

2.1.2 One-Class Support Vector Machine (OSVM)

The idea of OSVM (One-class Support Vector Machine [23]) is to construct a hypersphere shaped decision boundary with minimal volume around samples of $A$ in a specific feature space and, by this, to distinguish all other possible documents of an unknown authorship. If $D_U$ falls inside this hypersphere, $D_U$ is accepted ($U = A$), otherwise rejected. In existing AV and AA works, OSVM served as a baseline (for example, [2, 26]) or as the core method [33].

2.1.3 Local Outlier Factor

Another unary classification algorithm, which originally was constructed for finding outliers in large databases is LOF (Local Outlier Factor [3]) which, similarly to OCNN, also employs nearest neighbor

\footnote{According to the literature [40], Stamatas et al. were the first researchers, who discussed AV in the context of natural language texts in their paper [41] published in 2000. AV, therefore, can be seen as a young field in contrast to AA, which dates back to the 19th century [16].}
distances. LOF uses a sophisticated strategy for comparing the distances between \( D_U \) and its \( k \)-nearest neighbors to the distances between these neighbors and their \( k \)-nearest neighbors. The final score LOF returns is a quotient, derived from all these distances, which becomes larger the more \( D_U \) is an outlier.

### 2.1.4 Isolation Forest

Another unary classifier, which gained much attention in recent years, is IF (Isolation Forest [29]). Similarly to its counterpart Random Forest\(^1\), IF builds multiple binary trees that separate the feature space recursively. Each node divides its child nodes based on a randomly selected feature and threshold. Assuming that outliers are only “few and different” [29], the idea is that instances placed deeper in a tree are less likely outliers. The acceptance of \( D_U \) to be a member of the target class \( \mathcal{A} \) depends on its corresponding depth, averaged over the trees. Neal et al. [32] proposed an AV approach that works on top of IF.

### 2.2 Existing AV Approaches

During 2013–2015, the organizers of the PAN\(^2\) workshop held three AV competitions [22, 39, 40], which attracted attention among the AV community and led to a noticeable increase of proposed approaches in this field. In the following, we give a brief overview regarding a number of existing AV methods which, at least partially, achieved promising results within the PAN competitions.

In 2013, Seidman [38] proposed a successful AV method named GenIM (General Impostors Method) which is a slight variation of the well-known Impostors approach introduced by Koppel and Schler [28]. GenIM works in two steps. First, so-called impostor documents are gathered that aim to represent the counter class of \( \mathcal{A} \), namely \( \neg\mathcal{A} \). Second, a feature randomization technique is applied iteratively to measure the similarity between pairs of documents. If, given this measure, a suspect is picked out from among the impostor set with sufficient salience, then the questioned document \( D_U \) is considered to be written by this author, otherwise not [28]. GenIM was the overall winning approach of the PAN-2013 AV competition [22] in terms of \( F_1 \) and was ranked second in terms of AUC. In 2014, Khonji and Iraqi [24] proposed a slightly modified version of GenIM, which they named ASGALF\(^3\). The authors adapted a modified min-max(\( \cdot \))\(^4\) similarity measure as well as a larger set of features including function words, word shapes, and part-of-speech tags. ASGALF was the overall winning approach of the PAN-2014 AV competition [40].

In 2015, Bagnall [1] proposed a method based on a character-level RNN, which was not only the overall winning approach at the PAN-2015 AV competition [39] but also the first attempt to apply deep learning in the context of AV. Similarly to GenIM, the approach of Bagnall also requires a corpus \( \mathcal{C} = \{\rho_1, \rho_2, \ldots, \rho_n\} \) with \( \rho_i = (D_{U_i}, D_{A_i}) \), where the ratio of matching (Y) and non-matching (N) authorships must be known beforehand. The method can be roughly split up into four steps. The first step is to train language models\(^5\) (LM) for all known document sets \( D_{A_1}, D_{A_2}, \ldots, D_{A_n} \), which results in \( LM_1, LM_2, \ldots, LM_n \). As a second step, each unknown document \( D_{U_i} \) is attributed against all \( n \) trained language models. For this, a score (more precisely, the mean cross entropy) between \( D_{U_i} \) and each \( LM_j \) is calculated, which describes how “well” \( LM_j \) predicts \( D_{U_i} \). In the third step, all scores across the problems are normalized, in order to overcome possible variances among the learned language models. In the fourth step, the normalized scores are ranked and transformed into similarity scores. Based on the \( Y/N \)-ratio of \( \mathcal{C} \), the threshold to accept or reject unknown documents is then determined. For example, if \( \mathcal{C} \) is balanced\(^6\) (which was the case for the PAN-2015 AV corpora) then the method uses the median of the similarity scores as a threshold. One advantage of Bagnall’s approach is that it considers the entire document as a sequence of characters and automatically learns patterns to distinguish between authors. By this, defining handcrafted distances

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\(^1\) Random Forest is a well-known classification algorithm, widely used for n-ary classification tasks.

\(^2\) PAN is a series of scientific events and shared tasks on digital text forensics.

\(^3\) ASGALF stands for “A Slightly-modified GI-based Author-verifier with Lots of Features” [24].

\(^4\) Also known as the Ruzsinszky measure.

\(^5\) Technically, language models considered in Bagnall’s method are character probability distributions.

\(^6\) In a balanced corpus, the verification problems with matching (Y) and non-matching (N) authorships are evenly distributed.
features is avoided. However, since the method discriminates between multiple (known) authors, it better fits to the category of AA instead of AV methods (Dwyer [6] also made this observation). This and the fact that we were not able to reproduce this complex approach led to our decision to exclude it from our evaluation.

In 2015, Hürlimann et al. [17] proposed their novel AV approach GLAD\(^1\), which deliberately discards the idea to model an outlier class \(\neg A\) by collecting impostor documents. Instead, GLAD considers a training corpus \(C = \{\rho_1, \rho_2, \ldots, \rho_n\}\), where each verification problem \(\rho = (\hat{D}_U, \hat{D}_A)\) is labeled either as \(Y\) or \(N\). Given \(C\), GLAD constructs for each \(\rho \in C\) (not each document in \(\rho\)) a feature vector consisting of 24 features. Here, the features were obtained individually from \(\hat{D}_U\), \(\hat{D}_A\) or simultaneously from both (Hürlimann et al. denote these as “joint features”). After representing each \(\rho_i\) in the feature space, the authors train a binary SVM to separate the space such that \(\hat{D}_U\) is accepted or rejected depending in which subspace it falls.

In 2018, Halvani et al. [10] proposed their AV method OCCAV\(^2\), which also avoids the idea to model a counter class \(\neg A\) and is even independent of a training corpus. OCCAV is inspired by the unary classification algorithm OCNN. However, instead of constructing feature vectors from the documents, here, all texts are represented as compressed byte streams using the Prediction by Partial Matching (PPMd) algorithm. By this, a verification problem \(\rho = (\hat{D}_U, \hat{D}_A)\) is transformed into \(\hat{\rho} = (\hat{D}_U, \hat{D}_A)\), where all involved documents are compressed. Another difference to OCNN is that instead of using a standard distance function, OCCAV relies on the so-called Compression Based Cosine, which measures dissimilarities between compressed documents. Given this measure and the compressed documents in \(\hat{\rho}\), the method computes dissimilarities between \(\hat{D}_U\) and each \(\hat{D}_A \in \hat{D}_A\). Next, \(\hat{D}_{\text{near}} \in \hat{D}_A\) is selected, which has the smallest dissimilarity \(d_{\text{min}}\) to \(\hat{D}_U\). Then, dissimilarities between \(\hat{D}_{\text{near}}\) and each \(\hat{D}_j \in \hat{D}_A \setminus \{\hat{D}_{\text{near}}\}\) as well as their average \(d_{\text{avg}}\) are computed. If \(d_{\text{min}} < d_{\text{avg}}\) holds, then the unknown document \(\hat{D}_U\) is assumed to be written by \(A\).

### 3 Analysis

With the increasing number of proposed AV approaches, the wish arose to compile a systematic characterization to enable a better comparison between the methods. In 2004, Koppel and Schler [26] described, for the first time, the connection between unary classification and AV. In 2008, Stein et al. [42] provided an overview of important algorithmic building blocks for AV where, among others, they also formulated three AV problems as decision problems. In 2014, Potha and Stamatatos [34], introduced specific properties that aim to characterize AV methods. However, a deeper look on previous attempts to organize the field of AV reveals a number of misunderstandings, in particular, when it comes to draw the borders between unary and binary AV approaches. In the following, we analyze these misunderstandings and propose redefinitions as well as new AV properties. We show that in fact there are not only two (unary/binary) but three possible categories of AV methods and that their categorization solely depends on the way how the acceptance criterion is determined.

#### 3.1 Determinism of results

A fundamental property of any AV method, especially in the context of evaluation, is whether it behaves deterministically or non-deterministically. AV approaches such as [17, 18, 34] always generate the same output for the same inputs, i.e., these methods are deterministic. In contrast, non-deterministic AV methods as proposed in [15, 26, 32, 35, 38] involve randomness (for instance, subsampling of the feature space or the number of impostors) which, as a consequence, might distort the evaluation since every run on a (training or test) corpus very likely leads to different results. Therefore, it is indispensable to perform multiple runs and to consider the average and dispersion of the achieved results for a reasonable and robust comparison between different AV approaches.

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\(^1\)Groningen Lightweight Authorship Detection.

\(^2\)One-Class Compression Authorship Verifier.
3.2 Optimizability

Optimizability is another property of an AV method, which affects the dependency on a training corpus. We define an AV method as **optimizable** if, according to its design, it offers adjustable hyperparameters that can be tuned against a training corpus, given an optimization method (e.g., grid or random search). Such hyperparameters might be, for instance, the selected distance/similarity function, the number of neurons/layers in a neural network, the chosen kernel method of an SVM, the selected feature categories, or adjustable weights and thresholds. The majority of existing AV methods in the literature (including [5, 7, 15, 28, 34]) belong to this category. On the other hand, if a published AV approach involves hyperparameters that have been entirely fixed such that there is no further possibility to improve its performance from outside (without deviating from the definitions in the publication of the method), the method is considered to be **non-optimizable**. Obviously, non-optimizable AV approaches are easier to reproduce, as we can discard the dependency on a training corpus. Among the proposed AV methods in the respective literature, we only identified three approaches [10, 20, 44] that belong to this category.

3.3 Model Category (Unary versus Binary)

Even though AV clearly represents a unary classification problem [17, 26, 34, 36, 42], one can observe in the literature that sometimes it is interpreted as unary [19, 20, 32, 34] and sometimes as binary [25, 28, 30, 44]. We define the way an AV approach is modeled by the phrase **model category**. However, before explaining this in more detail, we first have to recall what, according to the literature, unary classification exactly represents. For this, we list the following verbatim quotes, which characterize unary classification, as can be seen, almost identically (emphasized by us):

- “In one-class classification it is assumed that only information of one of the classes, the target class, is available. This means that just example objects of the target class can be used and that no information about the other class of outlier objects is present.” [43]
- “One-class classification (OCC) […] consists in making a description of a target class of objects and in detecting whether a new object resembles this class or not. […] The OCC model is developed using target class samples only.” [37]
- “In one-class classification framework, an object is classified as belonging or not belonging to a target class, while only sample examples of objects from the target class are available during the training phase.” [19]

Note that in the context of authorship verification, the **target class** refers to the known author A such that for a document D_U of an unknown author U the task is to verify whether U = A holds.

One of the most important requirements of any existing AV method is a decision criterion, which aims to accept or reject a questioned authorship. A decision criterion can be expressed through a simple threshold \( \theta \) or a more complex decision model \( \theta_M \). As a consequence of the above statements, the determination of \( \theta \) or \( \theta_M \) has to be performed solely on \( D_A \), otherwise the AV method cannot be considered to be unary. However, our conducted literature search regarding existing AV approaches revealed that there are uncertainties, how to precisely draw the borders between unary and binary AV methods (for instance, [2, 34, 36]). Nonetheless, few attempts have been made to distinguish both categories from another perspective. Potha and Stamatatos [36], for example, categorize AV methods based on their characteristics being either **intrinsic** or **extrinsic** (emphasized by us):

1. “Verification models differ with respect to their view of the task. Intrinsic verification models view it as a one-class classification task […]. Such methods […] do not require any external resources.” [36]
2. “On the other hand, extrinsic verification models attempt to transform the verification task to a pair classification task by considering external documents to be used as samples of the negative class.” [36]

While we agree with (2), the former statement (1) is unsatisfactory, since intrinsic verification models are not necessarily unary. The AV approach GLAD [17], for instance, directly contradicts the above statement. Here, the authors
A similar contradiction to the statement of Potha and Stamatos can be observed in the paper of Jankowska et al. [18], who introduced the so-called CNG approach that resembles the unary k-centers algorithm [43]. CNG is intrinsic in that way that it considers only $\mathbb{D}_A$. On the other hand, the decision criterion which, in this specific case is a threshold $\theta$, is determined on a set of verification problems, labeled either as $Y$ or $N$ (“external resources”). Therefore, CNG is in conflict with the unary definition mentioned above. In a subsequent paper, however, the authors refined their CNG approach and introduced an ensemble based on multiple $k$-centers [19]. This time, $\theta$ was determined solely on the basis of $\mathbb{D}_A$ such that the modified approach can be considered as a true unary AV method, according to the aforementioned statements.

In 2004, Koppel and Schler [26] presented the Unmasking approach in their paper “Authorship Verification as a One-Class Classification Problem”, which, according to the authors, represents a unary AV method. However, if we take a closer look at the learning process of Unmasking, we can see that it is based on a binary SVM classifier, which consumes feature vectors labeled as $Y$ and $N$. Here, the task of the SVM is to classify the generated curves according to the two classes same-author and different-author. Unmasking, therefore, cannot be considered to be unary, as the decision is not based solely on the documents within $\mathbb{D}_A$.

It should be highlighted again that these approaches are binary and intrinsic since their decision criteria are determined on a training corpus labeled with $Y$ and $N$ in a binary manner (binary decision regarding problems with known $Y$ and $N$ labels) while regarding the verification they consider, in an intrinsic manner, only $\mathbb{D}_A$. A crucial aspect, which might have lead to misperceptions regarding the model category of these approaches in the past, is the fact that two different class domains are involved. On the one hand, there is the class domain of authors, where the task is to distinguish $A$ and $\neg A$. On the other hand, there is the elevated or lifted domain of verification problems, which either falls into class $Y$ or class $N$. The training phase of binary-intrinsic approaches is used for learning to distinguish these two classes, and the verification task can be understood as putting the verification problem as a whole into class $Y$ or class $N$, whereby the class domain of authors fades from the spotlight.

In contrast to binary-intrinsic approaches, there exist also AV approaches that are binary and extrinsic (for example [14, 24, 28, 35, 44]) as these methods use external documents during a potentially existing training phase and – more importantly – during testing. In these approaches, the decision between $A$ and $\neg A$ is put into the focus, where the external documents aim to construct the counter class $\neg A$.

Based on the observations above, we conclude that the key requirement (see illustration in Figure 1) to judge the model category of an AV method depends solely on the fact how its decision criterion $\theta$ or $\theta_M$ is determined:

1. An AV method is unary, if and only if its decision criterion $\theta$ or $\theta_M$ is determined solely on the basis of the target class $A$. As a consequence, an AV method cannot be considered to be unary if documents not belonging to $A$ are used to define $\theta$ or $\theta_M$.

2. An AV method is binary-intrinsic, if its decision criterion $\theta$ or $\theta_M$ is determined on a training corpus comprising verification problems labeled either as $Y$ or $N$ (in other words documents of several authors). However, once the training is completed, a binary-intrinsic method has no access to external documents anymore such that the decision regarding the authorship of $\mathbb{D}_U$ is made on the basis of the reference data of $A$ as well as $\theta$ or $\theta_M$.

3. An AV method is binary-extrinsic, if its decision criterion $\theta$ or $\theta_M$ is determined on the basis of external documents that represent the outlier class $\neg A$ (the counterpart of $A$). Here, it is not relevant whether a training corpus was used to optimize $\theta$ or $\theta_M$. As long as the method has access to documents of $\neg A$, it will remain binary-extrinsic.

It should be highlighted that unary AV methods (for instance, [11, 32, 34]) are not excluded to be optimizable. As long as $\theta$ or $\theta_M$ is not part of the optimization, the model category of the method
Learn $\theta$ or $\theta_M$ using only reference data of the target class $A$.

Learn $\theta$ or $\theta_M$ on a training corpus comprising verification problems labeled as $Y$ and $N$.

Learn $\theta$ or $\theta_M$ given external data that explicitly models the outlier class $\neg A$.

Figure 1: The three possible model categories of authorship verification approaches. Here, $\mathcal{U}$ refers to the instance (for example, a document or a feature vector) of the unknown author. $A$ represents instances of the target class (known author) and $\neg A$ the outlier class (any other author). $Y$ and $N$ denote the regions of the feature space where, according to a training corpus, the authorship holds or not. In the binary-intrinsic case, $\rho$ denotes the verification problem (subject of classification).

remains unary. The rationale behind this is that hyperparameters might influence the resulting performance of a unary AV method, while the decision criterion itself remains unchanged.

3.4 Implications

Each model category has its own implications regarding prerequisites, evaluability, and applicability.

3.4.1 Unary AV Methods

One advantage of unary AV methods is that they do not require a specific document collection strategy to construct the counter class $\neg A$, which reduces their complexity. Moreover, a training corpus is not required, at least if the method is non-optimizable (for example, OCCAV [10]. On the downside, the choice of the underlying machine learning model of a unary AV method is restricted to unary classification algorithms or also unsupervised learning techniques, given a suitable decision criterion. However, a far more important implication of unary AV approaches concerns their performance assessment. Since unary classification (not necessarily AV) approaches depend on a fixed decision criterion $\theta$ or $\theta_M$, performance measures such as the area under the ROC curve (AUC) are meaningless. Recall that ROC analysis is used for evaluating classifiers, where the decision threshold is not finally fixed. ROC analysis requires that the classifier generates scores, which are comparable across classification problem instances. The ROC curve and the area under this curve is then computed by considering all possible discrimination thresholds for these scores. While unary AV approaches might produce such scores, introducing a variable $\theta$ would change the semantics of these approaches. Since unary AV approaches have a fixed decision criterion, they provide only a single point in the ROC space. To assess the performance of a unary AV method it is, therefore, mandatory to consider the confusion matrix that leads to this point in the ROC space.

3.4.2 Binary AV Methods

If we design a binary (intrinsic or extrinsic) AV method, we can choose among a variety of binary and $n$-ary classification models. However, if the choice falls on a binary-extrinsic method, a strategy has to be considered, in order to collect representative documents for the outlier class $\neg A$.  

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1 Receiver Operating Characteristic.
2 For example: Support vector machines, logistic regression or perceptron.
3 For example: Naive Bayes, random forests or a variety of neural networks.
Methods such as [28, 35, 44] rely on search engines for retrieving appropriate documents, which might refuse their service if a specified quota is exhausted. Additionally, the retrieved documents make these methods inherently non-deterministic. Moreover, as can be observed in [22, 40] (as well as in our evaluation in Sec. 4) such methods cause relatively high runtimes. Using search engines also requires an active Internet connection, which might not be available or even allowed in specific scenarios. But even if we can access the Internet to retrieve documents, there is no guarantee that the true author is not among them. With these points in mind, the applicability of binary-extrinsic methods in real-world cases i.e., forensic settings, remains questionable. On the other hand, if we consider to design a binary-intrinsic AV method, it should not be overlooked that the involved classifier learns nothing about individual authors but only similarities or differences that hold in general for Y and N verification problems [28].

4 Evaluation

Based on our definitions in Sec. 3, we investigate the applicability of unary, binary-intrinsic and binary-extrinsic AV methods. First, we describe which existing AV methods as well as generic unary classification approaches were considered for our evaluation. Afterwards, we explain which corpora were compiled for the task.

4.1 Existing AV Approaches

To assess the performance of AV methods based on our criteria, we reimplemented 11 existing AV approaches that have shown their potentials in existing studies as well as in the three PAN AV competitions from 2013–2015. More precisely, we reimplemented two binary-extrinsic (GenIM [38] and NNCD [44]), five binary-intrinsic (COAV [12], AVer [13], GLAD [17], ProfileAV [34] and Unmasking [26]) and four unary AV approaches (DistAV [20], CNG [19], MOCC [11] and OCCAV [10]).

Note that in the original version of both binary-extrinsic approaches GenIM and NNCD, the authors proposed to use search engine queries to generate impostor documents that are needed to model the counter class \( \neg A \). However, due to quota limits, we decided to use an alternative strategy in our implementations. Let \( C = \{\rho_1, \rho_2, \ldots, \rho_n\} \) denote a corpus. For a given verification problem \( \rho_i = (D_U, D_A) \in C \), we choose all \( D_U_j \) in \( C \) with \( i \neq j \) as the impostor set \( U \). However, it should be highlighted that in GenIM, the number of impostors is a hyperparameter such that the resulting impostor set is a subset of \( U \), whereas in NNCD all \( U_j \in U \) are considered. Although our strategy is not flexible like using a search engine, it has one advantage that here it is assumed\(^1\) that the true author of an unknown document is not among the impostors, since in our corpora we know the user names of those who have written all documents.

4.2 Generic Unary Classification Approaches

In addition to the reimplemented unary AV methods, we also considered the four generic unary classification algorithms OCNN, OSVM, LOF and IF (introduced in Sec. 2) and adapted them to the AV task. To ensure a fair and equal setting, all classifiers were provided with the same set of features which, according to the literature in AV and AA, have been proven to perform very well. The set of features consists of character \( n \)-grams (with \( n \in \{2,3,4\} \)), punctuation marks and function words. However, since instead of raw strings the four algorithms require numerical feature vectors as an input, we represent all extracted features according to their relative frequencies in the documents. Instead of selecting the top most frequent features, which is the case in existing AV approaches such as CNG [19] or ProfileAV [34], we used all occurring features in the texts. Regarding the two distance-based methods OCNN and LOF, we decided to use the Manhattan distance, which has been applied successfully in previous authorship analysis studies (for example, [4, 8, 13, 21, 27]).

\(^1\)Note that we cannot be sure if two or more user names in fact refer to the same author.
4.3 Corpora

As a data basis for our evaluation, we compiled two corpora\(^1\). The first corpus represents a collection of 4,000 documents (aggregated postings, crawled from Reddit) written by 1,000 authors. The second corpus is a collection of 7,000 documents (aggregated product reviews, extracted from the Amazon product data corpus [31]) written by 1,400 authors. After aggregating the documents, we split both datasets into training \( (C_{\text{Reddit}}^{(tr)}, C_{\text{Amazon}}^{(tr)}) \) and evaluation corpora \( (C_{\text{Reddit}}, C_{\text{Amazon}}) \) and resampled the documents to construct balanced corpora with a bigger number of verification problems. As a result of the resampling procedure, \( C_{\text{Reddit}}, C_{\text{Reddit}}, C_{\text{Amazon}}^{(tr)} \) and \( C_{\text{Amazon}} \) ended up with 600, 1,400, 800 and 2,000 verification problems, respectively.

4.4 Results

After tuning hyperparameters of all optimizable approaches on the training corpora based on the described training procedure in the respective literature, we applied the learned models together with the non-optimizable methods on both evaluation corpora \( C_{\text{Reddit}} \) and \( C_{\text{Amazon}} \). The results regarding all approaches are listed in Table 1. Since we do not limit ourselves to one specific performance measure, we report for each method the outcomes TP, FN, FP, and FN of the corresponding confusion matrix. However, to enable a better comparison, we also list the following “single number” evaluation metrics: Accuracy, \( F_1 \) and Cohen’s \( \kappa \), where the latter is a relatively new performance measure in the context of AV, proposed by Halvani et al. in [9].

A variety of observations can be inferred from Table 1. In particular, the majority of binary-intrinsic AV methods tend to outperform both binary-extrinsic and unary approaches. GLAD, which is the top performing approach on both corpora, demonstrates that binary-intrinsic approaches are very effective, even though the AV task itself represents an unary classification problem. The two other binary-intrinsic methods \( \text{AVeer} \) and \( \text{COAV} \) also achieve high results, but differ from GLAD in several important aspects. \( \text{AVeer} \) and \( \text{COAV} \) rely both on simple similarity functions that accept or reject the authorship of unknown documents according to a scalar threshold. GLAD, on the other hand, is based on an SVM, which is widely known to be a strong classifier. An explanation why GLAD is superior might be that the discrimination ability of a single threshold is not fine-granular enough, compared to the hyperplane constructed by the SVM, which separates a 24-dimensional feature space in a non-linear\(^2\) way. Another (or an additional) explanation could be that, in contrast to \( \text{AVeer} \) and \( \text{COAV} \), GLAD makes use of several joint features (see Sect. 2.2), which might capture better differences or similarities between the documents.

Furthermore, we can see from Table 1 that binary-extrinsic approaches also perform very well, in particular GenIM. This is consistent with the findings in previous studies such as [19, 25, 34]. The high results regarding GenIM also indicate that considering static corpora to generate impostor documents is a suitable alternative to search engine queries.

When comparing the results of all methods on \( C_{\text{Reddit}} \) and \( C_{\text{Amazon}} \) to each other, we can also see that the majority of the examined AV approaches perform more or less stable (GLAD, COAV, DistAV and IF even have exactly the same rankings on both corpora). However, one exception is the binary-extrinsic method NNCD, which performs quite well on \( C_{\text{Reddit}} \), but is among the worst three approaches on the \( C_{\text{Amazon}} \) corpus. Unfortunately, there is no clear explanation, if this is caused by the bigger number of available impostors in \( C_{\text{Amazon}} \) (here, each \( D_{U1} \) is confronted with 400 more impostors than in \( C_{\text{Reddit}} \)) or due to another reason. Therefore, we leave this open question for future work.

From the four examined unary AV approaches (DistAV, CNG, MOCC and OCCAV; without the generic unary classification algorithms), OCCAV yields the best results and performs quite stable on both corpora. Despite of the fact that OCCAV, which builds on top of \( \text{OCNN} \), belongs to the category of non-optimizable AV approaches, it seems to generalize very well. This is particularly important in real-world settings such as forensic cases, where training corpora with labeled data of the suspects are not always available.

\(^1\)All corpora and additional material will be available after publication of this paper.
\(^2\)GLAD utilizes the RBF kernel.
Table 1: Evaluation results for $C_{\text{Reddit}}$ and $C_{\text{Amazon}}$ sorted by Accuracy in descending order. Binary-intrinsic approaches are highlighted by purple, binary-extrinsic approaches by orange and unary approaches by green. Non-optimizable and non-deterministic AV methods are marked by † and *, respectively.

| Method          | Performance score | Confusion Matrix | Runtime         |
|-----------------|------------------|------------------|-----------------|
|                 | Accuracy  | $\kappa$  | $F_1$  | TP   | FN   | FP   | TN   | (hh:mm:ss) |
| $C_{\text{Reddit}}$ |          |      |      |      |      |      |      |          |
| GLAD [17]       | 0.826    | 0.653  | 0.827 | 579  | 121  | 122  | 578  | 18:06     |
| GenIM [38] (⋆)  | 0.805    | 0.610  | 0.768 | 451  | 249  | 24   | 676  | 5:21:54   |
| AVer [13]       | 0.776    | 0.553  | 0.769 | 521  | 179  | 134  | 566  | 0:59      |
| COAV [12]       | 0.770    | 0.540  | 0.736 | 449  | 251  | 71   | 629  | 0:39      |
| OCCAV [10] (†)  | 0.767    | 0.534  | 0.766 | 533  | 167  | 159  | 541  | 12:27     |
| NNCD [44] (†)   | 0.764    | 0.529  | 0.695 | 376  | 324  | 6    | 694  | 14:36:25  |
| ProfileAV [34]  | 0.728    | 0.457  | 0.732 | 519  | 181  | 199  | 501  | 1:15:55   |
| $C_{\text{Amazon}}$ |          |      |      |      |      |      |      |          |
| GLAD [17]       | 0.858    | 0.716  | 0.859 | 867  | 133  | 151  | 849  | 16:00     |
| AVer [13]       | 0.816    | 0.631  | 0.811 | 790  | 210  | 159  | 841  | 1:39      |
| GenIM [38] (⋆)  | 0.784    | 0.567  | 0.761 | 690  | 310  | 123  | 877  | 52:32     |
| COAV [12]       | 0.778    | 0.556  | 0.763 | 716  | 284  | 160  | 840  | 2:18      |
| LOF [3]         | 0.769    | 0.537  | 0.779 | 817  | 183  | 280  | 720  | 40:34     |
| OCCAV [10] (†)  | 0.757    | 0.514  | 0.769 | 811  | 189  | 297  | 703  | 12:07     |
| OCNN [23]       | 0.734    | 0.467  | 0.674 | 552  | 448  | 85   | 915  | 41:52     |
| Unmasking [26] (⋆) | 0.731    | 0.462  | 0.728 | 719  | 281  | 257  | 743  | 8:42      |
| ProfileAV [34]  | 0.722    | 0.443  | 0.719 | 714  | 286  | 271  | 729  | 1:48      |
| CNG [19]        | 0.713    | 0.426  | 0.750 | 863  | 137  | 437  | 563  | 23:25     |
| MOCC [11]       | 0.712    | 0.424  | 0.660 | 559  | 441  | 135  | 865  | 1:38      |
| OSVM [23]       | 0.677    | 0.353  | 0.560 | 411  | 589  | 58   | 942  | 1:39:11   |
| NNCD [44] (†)   | 0.604    | 0.208  | 0.349 | 212  | 788  | 4    | 996  | 15:52:22  |
| DistAV [20] (†) | 0.604    | 0.207  | 0.708 | 960  | 40   | 473  | 247  | 0:27      |
| IF [29] (⋆)     | 0.495    | -0.011 | 0.608 | 785  | 215  | 796  | 204  | 36:15     |

From all generic unary classification algorithms (OCNN, OSVM, LOF and IF), LOF achieves the highest result. One interesting point here is that LOF outperforms the closely related OCNN method, although both not only rely on the same features but also on the same distance function. We wish to highlight at this point that, according to the literature, this is the first time LOF has been applied to AV such that we recommend to investigate its potential in future work. Another observation that can be seen in Table 1 is that IF performs similar to a random guess. This is noteworthy as recently Neal et al. proposed an AV method in [32] that is very similar to our IF implementation, where the authors report a recognition accuracy exceeding 98% on the so-called CASIS3 corpus. However, since this corpus is not available online, we cannot investigate this issue in more detail.

When comparing the unary AV approaches against the generic unary classification algorithms, there is no clear separation of these to groups regarding their performance since their ranks in Table 1 are interweaved. There might be a little advantage for the dedicated AV methods compared to the generic algorithms since OCCAV is on average the best method within these two groups, and IF is clearly separated at the bottom.

1Our IF implementation is mostly based on the scikit-learn library.
2Center for Advanced Studies in Identity Science.
3An attempt to request the corpus directly from the authors was also not successful.
Regarding the performance measures listed in Table 1, several interesting observations can be made. For example, when looking at the performance results in the $F_1$-column, we can see that the ranking of the examined AV methods differs from those of Accuracy (and $\kappa$). The reason for this can be explained easily, when we consider the underlying formulas of both measures:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$F_1 = \frac{2TP}{2TP + FN + FP}$$

The given formula for $F_1$ is obtained from the given formula for Accuracy by replacing $TP + TN$ with $2TP$. Resulting Accuracy values will be greater than $F_1$ values if $TN > TP$ and smaller if $TN < TP$ holds. This also answers the question, why two AV methods that perform almost equally in terms of Accuracy (for example, NNCD vs. DistAV on the $C_{Amazon}$) have a significant difference regarding their $F_1$ values.

The difference between Accuracy and $F_1$ is more than a matter of interchangeable design choices. The design of the $F_1$ measure leads to the problem that resulting $F_1$ values can be quite misleading. For instance, if an AV method predicts always $Y$ (e.g., due to a weak threshold), $F_1$ will result in $\frac{2}{3}$ on a balanced corpus. In contrast, Accuracy will result in $\frac{1}{2}$, which can be interpreted as a coin toss. In the case of an AV method that predicts always $N$, $F_1$ will be 0 while Accuracy will result in $\frac{1}{2}$ again.

Putting the discussion to a more abstract level, the problem is that the measure $F_1$ ignores the true negatives (TN) in contrast to Accuracy (and $\kappa$). Ignoring TN is generally not reasonable in the context of AV, as it must be measurable if a method is able to correctly predict such cases, where the authorship does not hold. Based on these findings, we discourage to use $F_1$ for assessing the performance of AV methods.

An observation regarding Accuracy and $\kappa$ can be made when comparing the columns for Accuracy and $\kappa$ in Table 1 to each other. Both measures preserve the same ranking, and a closer look reveals that $\kappa$ has a linear relationship to Accuracy on balanced corpora (such as $C_{Reddit}$ and $C_{Amazon}$). The explanation for this can be shown based on the definition of $\kappa$:

$$n = TP + FN + FP + TN$$

$$p_0 = n^{-1}(TP+TN)$$

$$p_c = n^{-2}((TP+FN)(TP+FP) + (FP+TN)(FN+TN))$$

$$\kappa = \frac{p_0 - p_c}{1 - p_c}$$

For balanced corpora, $p_c$ results in 0.5 such that $\kappa = 2 \times \text{Accuracy} - 1$ holds. However, in cases where corpora are imbalanced, it makes more sense to use $\kappa$ instead of Accuracy, as the latter favors the majority class. A visual inspection of the behavior of both measures regarding imbalanced corpora is given in [9].

A closer look on the last column in Table 1 also reveals a number of issues that may require some consideration. Compared to the binary-intrinsic AV methods, the majority of the unary approaches obviously require more runtime. One exception here is DistAV, which needs on average $\approx 31$ seconds to process a whole test corpus. Binary-extrinsic approaches require even more runtime, compared to almost all unary approaches. A good trade-off between performance and runtime (which might be an important issue in the context of an IR system) can be observed for AVeer, followed by COAV.

## 5 Conclusion and Future Work

Based on a comprehensive literature review of numerous AV studies, we identified a number of misunderstandings regarding the different model categories of existing AV approaches, which have serious implications regarding their prerequisites, evaluability, and applicability. We defined clear criteria that aim to draw precise borders between the different categories of AV approaches and explained, which challenges occur in terms of evaluation, when an AV method is based on a fixed decision criterion. Given our definitions, we reimplementation a number of existing unary, binary-intrinsic and binary-extrinsic AV methods and assessed their performance on two large self-compiled
corpora, which we made available for the AV community. One of our observations was that specific unary AV methods can not only outperform their binary-intrinsic and binary-extrinsic counterparts but also perform stable across the different corpora. We have shown why the \( F_1 \) performance measure can be misleading in the context of authorship verification and also highlighted the connection between Accuracy and \( \kappa \), which occurs when the considered corpora are balanced.

Furthermore, we tested the applicability of four generic unary classification algorithms for the AV task, where all four were given exactly the same feature vectors (and in two cases the same distance function). It turned out that distance-based unary classifiers are able to outperform existing AV methods and achieve (at least partially) promising results. For the first time, we applied LOF in the context of AV, which not only outperformed OSVM (a commonly used baseline in existing AV studies) but also requires less runtime. Therefore, we recommend to consider LOF as a starting point for future AV approaches.

In the near future, we will expand our evaluation on more corpora and organize the field of authorship verification in more depth, through the definition of additional properties such as reliability, robustness and interpretability. Here, especially the latter is gaining more and more importance. Moreover, we plan to compile additional corpora in order to investigate the question, if the findings in this paper also hold in other corpora, which differ in terms of topic, genre and the language itself.

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