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# HOW “TROLL” ARE YOU? MEASURING AND DETECTING TROLL BEHAVIOR IN ONLINE SOCIAL NETWORKS

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## ABSTRACT

The detection of state-sponsored trolls acting in misinformation operations is an unsolved and critical challenge for the research community, with repercussions that go beyond the online realm. In this paper, we propose a novel approach for the detection of troll accounts, which consists of two steps. The first step aims at classifying trajectories of accounts’ online activities as belonging to either a troll account or to an organic user account. In the second step, we exploit the classified trajectories to compute a metric, namely “troll score”, which allows us to quantify the extent to which an account behaves like a troll. Experimental results show that our approach identifies accounts’ trajectories with an AUC close to 99% and, accordingly, classify trolls and organic users with an AUC of 97%. Finally, we evaluate whether the proposed solution can be generalized to different contexts (e.g., discussions about Covid-19) and generic misbehaving users, showing promising results that will be further expanded in our future endeavors.

**Keywords** social network · troll · misinformation

## 1 Introduction

Online Social Networks (OSNs) are a crucial constituent of societies and they represent a primary platform for individuals to debate social and political issues, as well as means to diffuse critical messages and promote propaganda. OSNs have seen a dramatic transformation from an aggregation medium to a complex ecosystem, where the border between offline and online realms is often indistinguishable [1]. Recent studies have also shown that the influence of discussions on OSNs goes beyond the online platform, and may as well have a notable impact on societies, e.g., undermining the integrity of political elections and public health [2, 3, 4, 5, 6].

In this context, accuracy, confidentiality, and authenticity of the shared content are key elements for a safe communication, and hence, for the well-being of societies. However, OSNs have been suffering from a lack of these elements, as their growth have been accompanied with an increase in the number of deceptive and fraudulent accounts that intentionally damage the credibility of online discussions [7]. The activity of such accounts is often associated to

online harms tied with the honesty and ethics of conversations, such as the proliferation of hate speech, incitement of violence, and dissemination of misleading and controversial content, as recently observed in debates concerning the Covid-19 pandemic [8, 9, 10, 11, 12]. Such fraudulent accounts are recognized as major threats to healthy online conversations, whose activity can potentially exacerbate division on societal issues and affect the sovereignty of elections [13, 14, 15, 16, 17].

In the political context, the Russian meddling in the online debate during the 2016 US Presidential election represents the most notable deceptive online interference campaign [18] [19]. The Mueller report [20] suggested that Russia was engaged in extensive attacks on the US election system in 2016 aimed at manipulating a voting event. The “sweeping and systematic” interference allegedly employed bots (i.e., automated accounts) and trolls (i.e., state-sponsored human operators) to spread politically biased (mis-)information [21]. To this end, the US Congress released a list of 2,752 Twitter accounts linked to Russia’s “Internet Research Agency” (IRA), known as Russian trolls. Following this occurrence, considerable research efforts for identifying fraudulent accounts and malicious activity on several social media platforms began. As of today, Twitter keeps continuously sanitizing its online community from malicious entities involved in information operations across diverse countries [22, 23] and different geopolitical events [24].

While there are several proven techniques for uncovering bot accounts [25, 26, 27, 28, 29, 30], the detection of troll accounts is currently an unsolved issue for the research community, due to several factors such as, e.g., the human character of trolls. Recent efforts have devised approaches for identifying trolls by leveraging linguistic cues and profile meta-data, or extracting features from the observed behavior such as the number of actions performed by an account daily [31, 32, 33, 34, 35]. While these approaches showed promising results, they suffer shortcomings either by being language-dependent (pointing to a specific transmitted spoken language that is solely linked with the trolls under investigation [36, 37]) or constrained to a single OSN (using profile meta-data and platform-specific information). These major limitations have given rise to research efforts investigating language- and content-agnostic approaches such as [38], which discerns troll accounts by uncovering the online incentives that influence their behavior.

In our work, we continue this research line and devise a novel approach to detect troll behavior based on the timeline of their online activities on the Twitter OSN. Specifically, we consider the sequences of users’ activities on Twitter, regardless of the content shared, the language used, and the linked metadata, to classify accounts in i) trolls or ii) organic users (from now on, simply *users*). The rationale of our approach is to exploit potential differences in the behavior of trolls and users when responding to the different feedback received by others. For this purpose, we consider both the actions performed by an account and the feedback received by others (e.g., re-sharing of a given message). We refer to the former as *active online activities*, and to the latter as *passive online activities*, i.e., activities where an account is passively involved. We demonstrate the validity of our intuition on the detection of Russian trolls involved in the interference of the 2016 US presidential election. By inspecting the sequences of active and passive online activities of users and trolls, we observe different clusters of behaviors shared by the two classes of accounts. We then evaluate whether the proposed approach can be effectively used for the identification of generic (i.e., not necessarily troll accounts) misbehaving users. For this purpose, we propose to detect accounts suspended in the discussion relative to the Covid-19 pandemic.

**Contribution of this work** The contributions of our work can be summarized as follows:

- We propose a novel approach based on Long short-term memory (LSTM) for classifying sequences of accounts’ online activities (we refer to the time series of active and passive activities as a *trajectory*). Our approach correctly identifies trolls’ and users’ trajectories with an AUC and an accuracy of 99%.
- We introduce a metric, namely the *Troll Score*, that allows us to quantify the degree to which an account behaves like a troll. We also propose a Troll Score-based classifier capable of detecting troll accounts with an AUC of 97% and an accuracy of 98%. With a comparative analysis, we show that our proposed Troll Score-based classification approach outperforms existing baseline approaches by a margin of 8% in terms of AUC.
- We perform an exploratory analysis to observe the sequence of activities performed by the accounts under scrutiny and we discover three distinct *behavioral* clusters populated by both trolls and users, where each cluster is determined by types of active and passive activities accounts engage in.
- We assess our proposed approach in the detection of generic misbehaving users (suspended accounts) involved in the Covid-19 discussions. Results show that our approach identifies suspended accounts with an AUC of around 80%.

## 2 Related Work

In this Section, we discuss research focusing on the automated detection of malicious accounts operated by trolls, and in particular, on the troll farm connected to the IRA [39]. Some of these efforts focused on the content (language, media, etc.) posted by trolls in order to identify and detect them. For example, [36] proposed a theory-driven linguistic research on Russian trolls language. Authors demonstrate how such deceptive linguistic signals might contribute in the accurate identification of trolls. [37] also proposed an automated reasoning mechanism used to hunt for trolls on Twitter during the Covid-19 pandemic in 2020, by leveraging a unique linguistic analysis based on adversarial machine learning and ambient tactical deception. In [40], authors proposed a deep learning solution to perform troll detection on Reddit, and analyzed the tweets content by applying natural language processing techniques. Other works considered fusing behavioral and content features. In [31], authors used both behavioral and linguistic features (profile features, behavioral features, stop word usage features, language distribution features, bag of words features) for the detection of Russian trolls. In [41], authors relied on deep learning techniques merging content and behavior information. Other approaches relied on multimedia analysis approaches with text, audio, and video-analysis assistance to detect improper material or behavior [42, 43]. [42] devised an architecture for a platform for monitoring OSNs with the objective of automatically tracking malicious content, by analyzing images, videos, etc. In [43], authors attempt to capture disinformation and trolls based on the existence of a fire-arm in the images by using the Object Detection API. A shortcoming of these works is their dependence on the content posted by the accounts, and on the resulting extraction of linguistic features for the troll identification. Instead, in our work, we only rely on the online behavior of accounts, and more specifically, on the temporal sequence of online activities performed by an account, which presents an advantage over previous works as it is independent of language used or content shared.

Sequence analysis approaches have been proposed previously. For instance, in [44], the authors explore the temporal and semantic similarity in the sequence of shared content (i.e., tweet) of trolls, by considering text and time as features to categorize the troll population into subgroups. Moreover, in [38], authors proposed a solution that only relies on the sequence of users' activity on online platforms to capture the incentives the two classes of accounts (trolls vs. users) respond to. They detect troll accounts with a supervised learning approach fed by the incentives estimated via Inverse Reinforcement Learning (IRL). In [45], authors propose a model based on users' clickstream (i.e., sequence of online actions) to identify "clusters" of accounts with similar behavior. Our work is similar to above-mentioned works as it also focuses on identifying troll accounts based on their activity logs.

However, to the best of our knowledge, very few works have focused on identifying trolls by considering their activity as a sequence of actions such as [38, 44]. Such solutions, including our approach, do not use social network-specific information or linguistic characteristics, and hence, have the potential to be extended to other social media platforms and state-sponsored trolls operating in various scenarios. On the direction of these approaches, we propose a language- and content-agnostic method to identifying trolls, depending on the behavior and activities performed by the accounts on Twitter. Specifically, we propose a unique approach based on deep learning, and specifically LSTM, to classify the sequence of activities as either belonging to troll accounts or organic users. We further exploit the proposed model to quantify the extent to which an account behaves like a troll, a feature that is not available in previous works. We further note that our approach achieves higher performance in identifying troll accounts with respect to existing solutions.

## 3 Problem Formulation and Trajectory Definition

This Section delineates the objective of this work and defines the features, variables, and learning tasks of the proposed framework. As mentioned in Section 2, while existing approaches for identifying troll activities in OSNs rely on linguistic features and metadata, our proposed solution aspires to be agnostic both to the language and the social media platform under analysis. To achieve this aim, we propose to only use the sequences of accounts' online activities (referred to as trajectories) leveraging neither textual (or media) content the accounts shared nor metadata associated to their profile. In this work, we evaluate our approach with the Twitter OSN.

To mine the peculiar and distinctive characteristics of trolls' and users' online behavior on Twitter, we rely on (some of) the possible sharing activities they can perform (i.e., *active online activities*), such as generating an original post (i.e., *tweet*), re-sharing another post (i.e., *retweet*), commenting an existing post (i.e., *reply*), or mentioning another user in a post (i.e., *mention*). In addition, we also propose to consider the feedback the accounts receive from others (i.e., *passive online activities*), such as receiving a retweet (i.e., *being retweeted*), a reply (i.e., *being replied to*), or a mention (i.e., *being mentioned in a post*). In this paper, we leverage the sharing activities performed on Twitter, but the approach can be easily replicated on other OSNs such as Facebook, where we can similarly rely on posting, re-sharing, commenting, and mentioning activities.

The rationale behind considering both the actions performed by the accounts along with the received feedback is based on the assumption that trolls might execute their agenda regardless of others’ feedback, while organic users’ actions may be affected by the extent of endorsement received by the online community. For instance, a user might be more motivated to generate a new tweet when her/his content is re-shared by others, which is also view as a form of social endorsement [46, 47], or she/he is involved in others’ conversations. To encompass both the actions performed and the feedback received by the accounts, we framed the Twitter environment as a Markov Decision Process (MDP). This formulation was firstly introduced in [38] with the purpose of unveiling the incentives (in terms of rewards) driving trolls’ activity through an approach based on IRL.

In our work, and by leveraging the MDP formulation, we represent the observed behavior of every account with *states* and *actions*. A *state* represents the current situation of the account within the Twitter environment in terms of received feedback. An *action* indicates a sharing activity performed by the account. Every account can move from one state to another when performing an action. We refer to such a transition as a *state-action pair*. By considering the accounts’ timeline, we construct a *sequence* of state-actions pairs that reconstruct the (recorded) history of the account on Twitter. Accordingly, we define the problem of identifying troll sequences as a binary classification task, with two classes: *troll* (positive class) and *user* (negative class).

We consider four actions that can be performed by an account:

- Original tweet (tw): generate original content.
- Retweet (rt): re-share content generated by others.
- Interact with others (in): interact with other users by means of replies or mentions.
- No Action (no): the user does not perform any action.

For what pertains to states, we consider three possible feedback that a Twitter account can receive:

- Retweeted (RT): an original tweet generated by the account is re-shared.
- Interacted with (IN): the account is involved by others by means of replies or mentions to account’s tweets.
- No Interaction (NO): no feedback is provided to the account.

Overall, there exists only 11 possible combinations of state-action pairs (state-action pair (NO, no) is not considered as it does not describe any activity) that form a sequence of an account. Note that an account can be only in one of the above-mentioned states and can perform only one action in any given state. It is also important noting that if an account does not react to the environment feedback, e.g., it does not perform *tw*, *rt* or *in*, it will be considered as silent, i.e., doing no action (*no*). Similarly, if an account keeps performing actions while not receiving any feedback, it will persist in the state *NO*. By extracting the state-action pairs of an account and time-ordering them, we form a sequence of online activities describing the behavior of troll and user accounts on Twitter. Section 5 details how we first classify these formed sequences as pertaining to either trolls or users, and then how we use these formed sequences to fulfill our objective, i.e., to identify troll accounts.

## 4 Data

The dataset used to evaluate our approach consists of tweets generated by user accounts and by accounts identified as trolls involved in the 2016 US election discussion over Twitter. Specifically, we consider the dataset described in [36, 32] collected by utilizing a set of keywords (detailed in [48]) related to the 2016 US election.

In such a dataset, we identified 342 troll accounts, selected from a list of 2,752 Twitter accounts designated as Russian trolls by the US Congress and that were publicly released during the investigation of Russian involvement in the US 2016 Presidential election. As for user accounts, we have considered a list of 1981 accounts that generated at least both 10 active online activities and 10 passive online activities (to be consistent with trolls’ activity) out of 1,166,760 users present in the dataset. Overall, the number of original tweets corresponding to the 342 troll accounts and 1981 user accounts is 246k and 1.2M, respectively.

## 5 Methodology

This Section details our proposed approach to identify troll accounts. Section 5.1 provides an overview of our framework, while section 5.2 describes the proposed methodology in more detail.

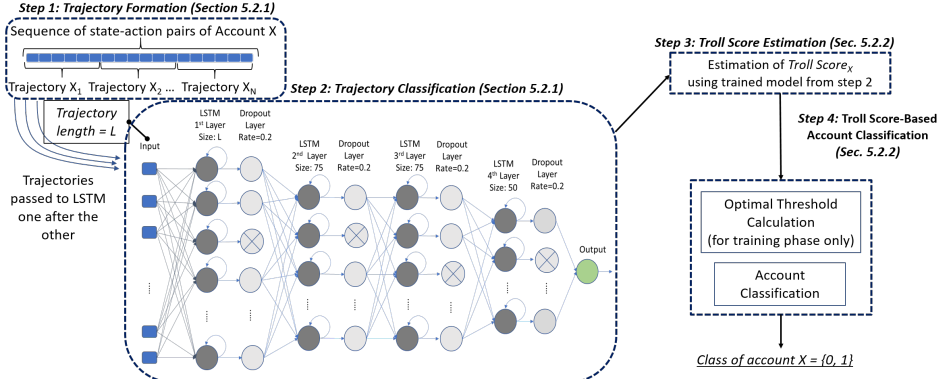


Figure 1: Overall Framework

## 5.1 Overall Framework

The proposed framework for the identification of troll accounts (see Figure 1) consists of four main steps:

- **Step 1: Trajectory Formation:** creation of trajectories that represent parts of a sequence of an account, where a trajectory is a time-sorted set of a pre-defined number of *state-action pairs*.
- **Step 2: LSTM-Based Trajectory Classification:** classification of the trajectories of state-action pairs into two classes, i.e., troll trajectories or user trajectories. To perform such a classification, we employ a Long Short-Term Memory (LSTM)-based classifier, from now on referred to as *LSTM-based Trajectory Classifier* (discussed in detail in section 5.2.1).
- **Step 3: Troll Score Estimation:** The *troll score* is computed as the ratio of number of trajectories classified as belonging to troll to that of all trajectories per account (described in detail in section 5.2.2).
- **Step 4: Troll Score-Based Account Classification:** classification of an account, i.e., *troll* or *user*, based on the troll score previously computed (described in detail in section 5.2.2).

For more clarity, we show in Fig. 5.1 an overview of our proposed framework. First, the sequence of online activities of an account is divided into several trajectories of state-action pairs of a pre-defined length. Second, an LSTM model fed by the extracted trajectories classifies these as either troll trajectories or user trajectories. Note that, in the training phase of the LSTM model, a trajectories extracted from a sequence of a troll is considered to have a label of a *troll trajectory*, while that extracted from a sequence of a user is given the label of a *user trajectory*. We employ deep learning and, more specifically, an LSTM model as we deal with time series data (i.e., sharing activities represented by state-action trajectories). After classifying trajectories of an account, a troll score of the account is computed as explained in *Step 3* and finally, in *Step 4*, based on the troll score, an account is classified as either a troll or a user. Note that to be able to distinguish the class of an account based on its troll score, a troll score threshold has to be defined, at which an account is either classified as a troll or as a user. We explain in detail how such a threshold is found in next sections.

## 5.2 Trolls Detection

We now discuss in more detail our proposed approach for the identification of troll accounts. In section 5.2.1, we describe the LSTM-based model used to classify trajectories of state-action pairs, while in section 5.2.2 we introduce the *troll score* metric and we detail the account classification approach. The code and scripts used to implement the methodological framework detailed below is freely available to the research community<sup>1</sup>.

### 5.2.1 LSTM-Based Model for Trajectory Classification

**Model Input:** The LSTM model takes in input a trajectory of a given length (i.e., a pre-defined number  $L$  of state-action pairs). To achieve this aim, two questions need to be answered: i) How to choose the value of  $L$ ?, and ii) Given a value for  $L$ , how to divide the sequence into trajectories? **How to choose the value of  $L$ ?** The choice of  $L$  is not trivial and it is in fact decisive. Considering a small value of  $L$  is desired from a computational point of view however a relatively small value for  $L$  might not be enough for the model to distinguish troll sequences from user sequences. On the contrary,

<sup>1</sup><https://github.com/FatimaEzzeddine/How-Troll-are-you-Measuring-and-Detecting-Troll-Behavior-in-Online-Social-Networks>

considering a relatively large value for  $L$  might not be feasible, as not every account might be largely engaged in online activities, i.e., not all the accounts might have a long sequence. For our approach, we performed a sensitivity analysis monitoring the performance of our model (in terms of several classification metrics) at varying  $L$ . We discuss this analysis in section 6.1.

**Given a value for  $L$ , how to divide the sequence into trajectories?** To form trajectories for trajectory classification, we consider non-overlapping parts of the sequence, i.e., we divide the sequence in  $L$ -long trajectories. For instance, for a trajectory length of 200, and a value of  $L = 100$ , 2 sequences each of length  $L$  are created and therefore considered for classification. Note that, for a given value of  $L$ , the number of sequences to classify per account differs. A larger  $L$  means lower number of sequences to classify while a smaller  $L$  means a higher number of sequences to classify. We will show the impact of this parameter in section 6.1.

### 5.2.2 Troll Score-Based Classification of Accounts

**Troll Score Definition** The objective of defining a *troll score* is to have a measure quantifying the extent to which an account behaves like a troll, i.e., to measure how much an account resembles a troll in its online sharing activity. We define the troll score of an account as the ratio between the number of trajectories classified as a troll by the LSTM model and the total number of trajectories of the account. The troll score, thus, ranges from zero to one, where a score close to one means a troll-like behavior and a score close to zero means a user-like behavior. To compute the troll score of a given account, we consider a sliding window of length  $L$  over the whole sequence of state-action pairs of the account under scrutiny. Such an approach allows each state-action pair to contribute to several trajectories.

**Troll score for Account Classification** To classify accounts based on their troll score, a threshold to distinguish the two distinct classes, i.e., trolls and users, is required. We compute this threshold as follows. First, the troll score of a subset of the accounts is found. Then, we iterate over all threshold values ranging from 0 to 1, with a step of 0.02, reporting the performance under each threshold value in terms of AUC. That is, we consider each value to serve as a threshold and classify accounts accordingly, where each value will result in a different classification of the accounts, and hence, a distinct performance. Finally, we select the threshold that provides the best AUC. For our evaluations, we test our approach with a 10-fold cross-validation.

## 6 Results and Discussion

In this Section, we first perform a sensitivity analysis comparing the performance of the LSTM-based trajectory classification approach in the case of trajectories composed of i) state-action pairs and ii) actions only. The objective here is to evaluate whether the states (i.e., received feedback) represent a beneficial information for the classification task. More specifically, the rationale is to understand if the feedback received by trolls and users, along with the way they react to such stimuli, might allow us to better discern these two classes of accounts with respect to leveraging only their performed actions. Then, we benchmark the trajectory classification approach based on LSTM comparing its performance to those of off-the-shelf machine learning models.

After validating the performance of the LSTM-based trajectory classification approach, we use it to compute the *troll scores* of the accounts under investigation. We then exploit the troll score to distinguish troll and user accounts and we compare the classification performance to other approaches proposed in literature. Moreover, based on the obtained results, we conduct an observational analysis to further investigate how the visited state-action pairs of trolls and users differ. Finally, we evaluate whether the proposed approach can be broadened to the detection of generic (not necessarily trolls) misbehaving users. We discuss results applying our approach on data from online discussions related to Covid-19 on Twitter with the objective of discerning misbehaving users (suspended accounts) and organic users (non-suspended accounts).

### 6.1 Trajectory Classification

This subsection presents the implementation details of our proposed LSTM model for trajectory classification and then discusses results comparing performance of our proposed model with *State-Action* pairs to that with *Actions* only, and the performance of our proposed model to off-the-shelf machine learning models.

#### 6.1.1 Implementation Details

Our proposed LSTM model for trajectory classification is composed of four LSTM layers, four dropout layers, and a dense layer. Each layer is followed by a Dropout Layer to reduce overfitting [49]. The *sigmoid* is used as activation function for both the hidden and output layers. We fine-tuned the hyper-parameters of our model with a random search.

Input	L	Trolls Trajectories	Users Trajectories
State-Action	50	64984	102101
	65	49975	78424
	80	40587	63643
	100	32457	50831
	150	21628	33795
	200	16230	25299
Action	50	7709	93721
	65	5927	72091
	80	4802	58593
	100	3819	46863
	150	2547	31267
	200	1920	23476

Table 1: Number of trajectories of trolls and users for each trajectory length  $L$ 

We encode trajectories to be fed into the LSTM model using *Label Encoding*, which consists of assigning an integer to each combination of state-action pairs. The entire model is trained by minimizing the binary cross-entropy with the Adam optimization algorithm [50].

### 6.1.2 State-Action vs. Action

To perform trajectory classification, we rely on the historical data of the accounts collected as described in Section 3. To evaluate our proposed approach, we build the trajectories of each of the accounts in two ways, considering state-action pairs sequences and considering only actions. Further, we consider five different values of the trajectory length  $L$ , ranging from 50 to 200, as shown in Table 1. Note that the overall number of trajectories changes with the value of  $L$ . We report in Table 1 the number of trajectories per every class of accounts in each of the cases (state-action pairs and only actions) and for all values of  $L$ . We further note that the number of sequences with *Action* is much lower than that for *State-Action* as trajectories of *Action* are formed with only 3 actions (*tw*, *rt* and *in*), and hence are much shorter than *State-Action* trajectories. We train and test our LSTM model in both cases, and report the results of a 10-fold stratified cross-validation. It should be noted that for the scenario with only *Actions* there is an imbalance between the number of sequences of trolls and users. To solve this issue, we employ the under-sampling technique [51, 52].

Figure 2(a) shows the AUC and accuracy of the LSTM-classifier with trajectories composed of (i) *State-Action* pairs and (ii) *Actions* only as functions of the trajectory length  $L$ . Results show that both classification metrics, and for all values of  $L$ , are higher with *State-Action* pairs than with *Actions* only. Specifically, with *State-Action* pairs, the AUC is around 99%, significantly higher than that with *Actions* only, which, in turn, fluctuates around 82%, for all values of  $L$ . In terms of accuracy, our proposed model reaches an accuracy of 97% with *State-Action* pairs while an accuracy of 92% with *Actions* only. This suggests that the *states* (i.e., feedback from the environment) represent a beneficial information for the accounts classification as, along with the *actions*, allow to achieve a better distinction between trolls and users if compared to the results achieved when considering trajectories based only on actions. From Fig. 2(a), we also note that varying the value of  $L$  has a minimal impact on model’s performance in both cases. In fact, the AUC of the LSTM-based approach reached 99% even when  $L$  is relatively short (e.g.,  $L = 50$ ). This finding shows that the proposed model, when considering *State-Action*, has the ability of correctly identifying trolls’ and users’ sequences even when little information about accounts’ online activity is available. This surprisingly high classification accuracy is probably due to the nature of our experimental design, which focuses on distinguishing the activity sequences of organic users from those of troll accounts. The latter, performing their agenda regardless of others’ feedback [38], present activity patterns naturally different with respect to legitimate users. While these differences might appear explicit in such a high-quality dataset, we do not expect the same results in a more challenging scenario (see Section 6.4).

We further evaluate the performance of our model in the two cases by considering other classification metrics such as Precision, Recall (or TPR), and F1 score. Figure 2(b) depicts these metrics for the different values of  $L$ . Results show that the model has a nearly perfect performance with *State-Action* considering all metrics (around 98%) with a slight increase in performance as  $L$  increases. On the contrary, the LSTM classifier with *Actions* only suffers from low performance, nearly 0%, in terms of Recall and F1, while precision ranges between 10% and 60% and increases as  $L$  increases. This further confirms our previous intuition in considering, in addition to actions, the feedback the accounts receive from the environment (i.e., states). Indeed, these results show that the states are essential to accurately classify the two classes of accounts, which suggests that trolls might react to online feedback differently from non-trolls. In the rest of our analysis, we will consider the model based on *State-Action* pairs, given that it has shown to be effective in discriminating users and trolls.

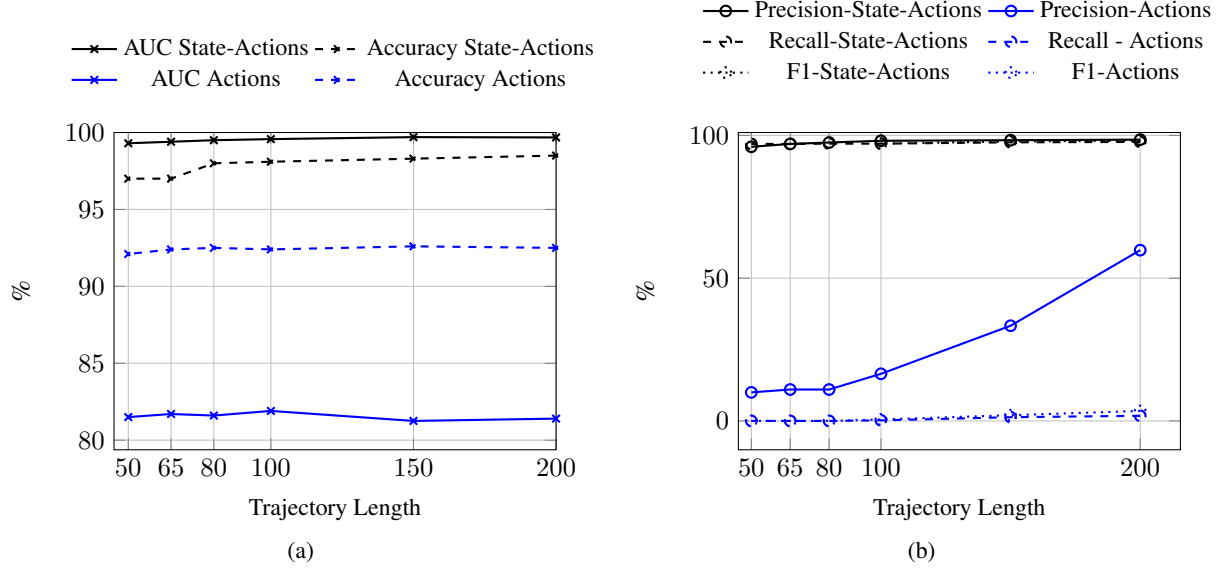


Figure 2: (a) AUC and Accuracy of the LSTM-based sequence classification approach with trajectories composed of state-action pairs and with actions only, and (b) Precision, Recall and F1-Score of the LSTM-based sequence classification approach with trajectories composed of state-action pairs and with actions only

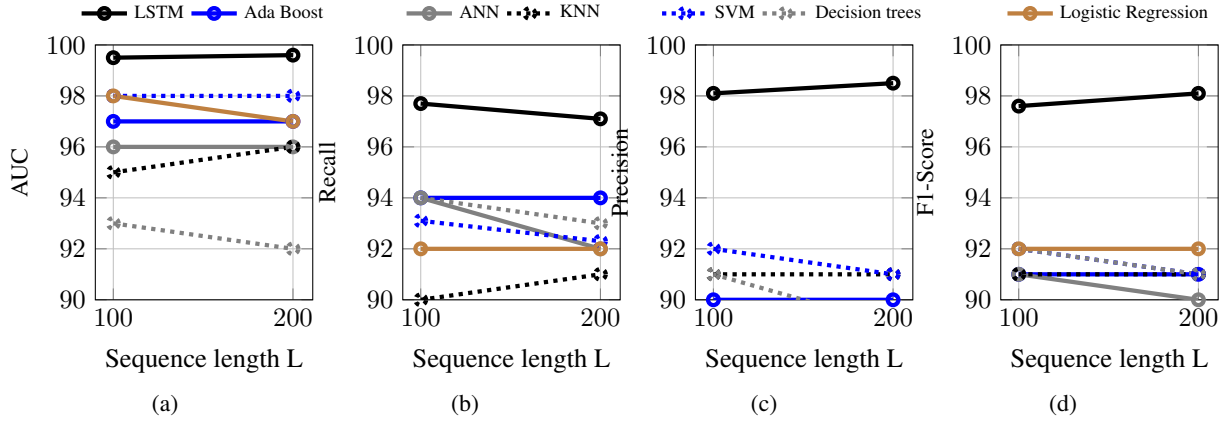
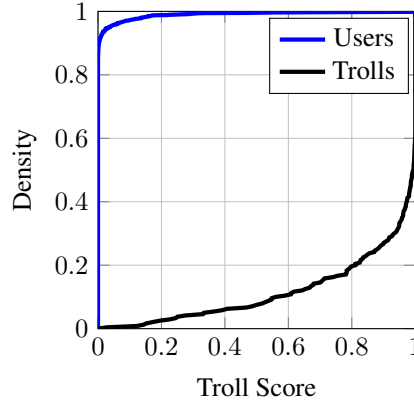


Figure 3: Comparison between the proposed LSTM-based approach and off-the-shelf machine learning models for trajectory classification in terms of (a) AUC, (b) Recall, (c) Precision and (d) F1-score

### 6.1.3 LSTM vs. Off-the-Shelf Machine Learning Models

We now compare the performance of our proposed LSTM-based model for trajectory classification to those of off-the-shelf machine learning models. Specifically, we consider Support Vector Machine (SVM), Artificial Neural Network (ANN), Decision Tree, Ada Boost, Logistic Regression, and K-Nearest Neighbors (KNN). Fig. 3 shows AUC, Recall, Precision, and F1-score of these models for  $L = 100$  and  $L = 200$ . For all metrics, and for both values of  $L$ , all approaches show a promising performance (e.g., AUC of 92% and higher), whereas our proposed LSTM-based approach achieves a near optimal performance (AUC of 99.5%), thus, outperforming all other models. More specifically, the LSTM-based approach shows 98% for Precision and Recall, significantly higher than that of other approaches, which do not exceed 92%. This indicates that trolls' and users' trajectories embed distinguishable patterns, which are more easily identifiable by models conceived to work with sequential data, such as LSTM, than other general purpose machine learning models.



Figure 4: Troll Score of user and troll accounts with  $L = 200$ 

## 6.2 Troll Score for Account Classification

We now concentrate our discussion on the classification of accounts. In this case, sequences are formed by sliding a window of length  $L$  over the entire trajectory by a step of one element. Note that in this case, two consecutive sequences overlap by  $L - 1$  elements. Moreover, the same element can be considered into several sequences, depending on its location along the trajectory. As previously discussed, the classification of the accounts is based on the *troll score* metric. The latter is computed for every account leveraging the classification of its trajectories extracted with a sliding window. Finally, the troll score of the account under scrutiny is compared to a *troll score threshold* (see section 5) to assign the account to one of the two classes of accounts (troll vs. user).

### 6.2.1 Troll Score of User and Troll Accounts

We first analyze the troll score computed for each account in our dataset. Figure 4 shows the Cumulative Distribution Function (CDF) of the troll score of user and troll accounts for  $L = 200$ <sup>2</sup>. Numerical results show that the CDF of the troll score of users shows a logarithmic growth (the CDF reaches 0.95 for a troll score of 0.02). This means that most of the users (95% of them) have an almost-zero troll score while the rest (remaining 5%) have a troll score of at most 0.2, which can be considered considerably low. On the contrary, the CDF related to the trolls follows an exponential growth (increases very slowly for low values of troll score and then increases exponentially for higher values of troll score). In particular, results show that 80% of the trolls have a troll score of at least 0.8. This shows that, on the one hand, a significant portion of the trolls are characterized by a high troll score. On the other hand, this also shows that a limited yet considerable portion of trolls have a relatively low troll score (e.g., 10% have a troll score of at most 0.5). This finding demonstrates that some of the trolls under analysis, specifically those characterized by a low troll score, exhibit a user-like behavior. To inspect in more detail the reasons behind the fact that some trolls are characterized by a low troll score, we perform an analysis to observe the visited state-action pairs of all accounts. We present this observational analysis in the following section.

### 6.2.2 Troll Score-Based Classification vs. Baseline

To test our approach, we validate it with a stratified k-fold ( $k=10$ ) cross validation. For every fold, the training set is employed to find the *optimal* troll score threshold (see Section 5.2.2), while the test set is used to evaluate the classification based on the troll score threshold selected in the training phase.

We compare the performance of our approach to the solution based on Inverse Reinforcement Learning (IRL) proposed in [38], which is the only existing language-agnostic approach that solely leverages the sequences of accounts' sharing activity. Based on the observed behavior of users and trolls, the IRL-based classification approach extracts the incentives driving their activity, in the form of numerical rewards, which are then used to classify the accounts with a supervised learning algorithm.

Table 2 shows AUC, Recall, Precision and F1-score of the Troll Score-Based approach and of the IRL-based approach for  $L = 200$ . For all metrics, IRL-based approach show a promising performance (e.g., AUC of 89.1%). However, our proposed Troll Score-based approach achieves an AUC of 97%, outperforming the IRL-based approach. More

<sup>2</sup>We omit showing the case with  $L = 100$  as results present same takeaways as for  $L = 200$ .

Metric	Troll Score-based	IRL-based
Accuracy	<b>98.7</b>	83
AUC	<b>97</b>	89.1
Precision	<b>96.6</b>	84.0
Recall	<b>94.5</b>	85.0
F1-Score	<b>95.5</b>	84.5

Table 2: Comparison between the proposed Troll Score-based approach and the IRL-based approach [38] for troll account identification

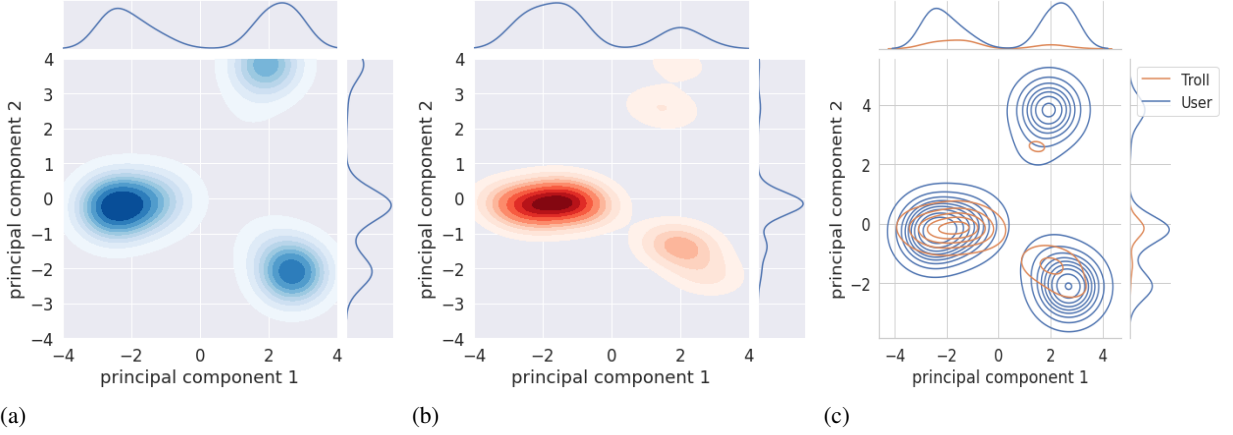


Figure 5: Clustering of accounts based on set of visited state-action pairs for (a) users, (b) trolls, and (c) users and trolls combined

specifically, the Troll Score-based approach shows 96% for Precision and 94% of Recall, significantly higher than the IRL-based classifier, which achieves 85% Recall and 84% Precision.

### 6.3 Behavioral Clustering and Troll Score

This section presents the analysis conducted to analyze the behavior of troll and user accounts in terms of their visited state-action pairs. A visited state-action pair means a state-action pair that is present in the trajectory of the account. The rationale behind this analysis is to examine whether trolls and users have distinct visited state-action pairs and how these are related with their troll score. Specifically, we evaluate whether the different classes of accounts could be grouped together in clusters based on the visited state-action pairs and, if clusters are observed, their relation with the troll score.

*Clustering based on visited state-actions:* We perform this clustering considering the visited state-action pairs. The set of features considered consists of 12 features (set of state-action pairs). The values of the features per account are either set to 1, if the account visited a state-action pair, or to 0 otherwise. We use the Principle Component Analysis (PCA) to perform a dimensionality reduction and we observe if any cluster emerges. In Figure 5, we show the results of a PCA with 2 components and we observe the appearance of three clusters both for users and trolls. In particular, Figure 5 shows a joint plot for users (5a), trolls (5b) and all accounts (5c). Figure 5(a) shows that users divide into three distinct clusters with slightly different distributions. Similarly, Fig. 5(b) shows three clusters for trolls, in which one cluster (cluster on the left) contains a major part of troll accounts while the other two clusters contain relatively lower fraction of trolls. For a better comparison, we display in figure 5(c) the joint plot of users and trolls combined, from which we can appreciate the emergence of three distinct *behavioral clusters*, where trolls and users coexist.

	Cluster 1	Cluster 2	Cluster 3
Users	977 (49.5%)	603 (30.43%)	401 (20.24%)
Trolls	256 (75.07%)	65 (19.06%)	20 (5.86%)

Table 3: Distribution of user and troll accounts in the three clusters

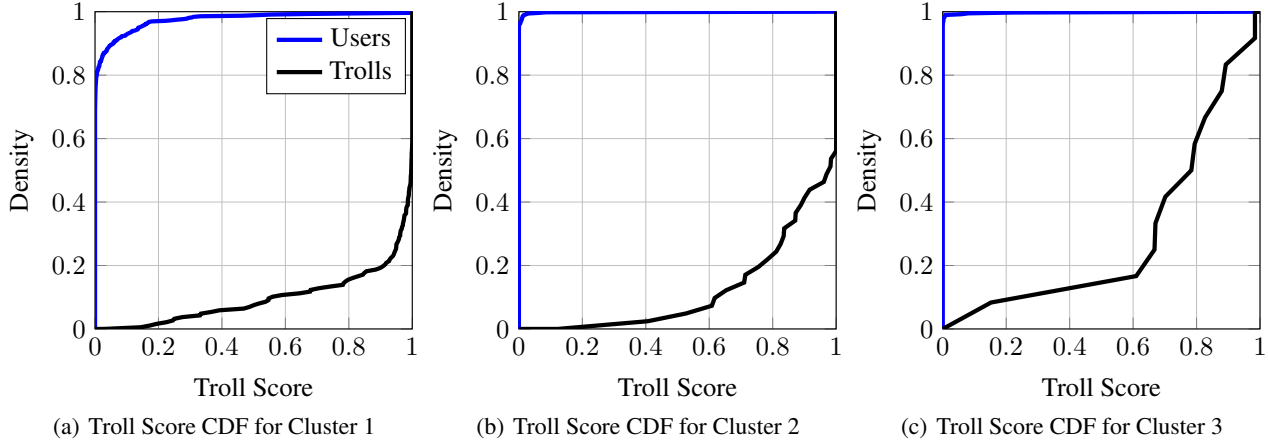


Figure 6: Troll Score of accounts in Cluster 1 (a), 2 (b) and 3 (c) with  $L = 200$

Table 3 reports the number of trolls and users present in each of the three clusters. Cluster 1 refers to the largest cluster (bottom left in figure 5), Cluster 2 refers to cluster on the bottom right, and Cluster 3 refers to the one on top right. In terms of visited state-action pairs, the clusters can be differentiated as follows:

- Cluster 1: Accounts in this cluster tweet or stay silent with any received feedback.
- Cluster 2: Accounts in this cluster tweet when no feedback is provided by the environment (state NT) or they retweet with any received feedback.
- Cluster 3: Accounts in this cluster tweet or interact with others (replying or mentioning) with any received feedback.

Our findings are consistent with [38] and show that most trolls (trolls in Cluster 1) tweet and retweet regardless of the received feedback, while a very little percentage of them (Cluster 3) participate in discussions by means of replies and mentions. This behavior is significantly different with respect to that of user accounts as they are distributed among the three clusters and tend to join in the dialogues and participate more in discussions.

*Troll Score CDF per Cluster:* We now evaluate the troll score of the accounts belonging to each of the cluster separately to inspect if differences in troll scores are present among the users of the various clusters, i.e., to inspect how the distribution of troll scores of users and trolls vary based on visited state-action pairs. Figures 6(a), (b), and (c) show the CDF of the troll score of accounts in Cluster 1, 2, and 3, respectively. Figures show that the CDF of troll score of users in all clusters has an *exponential* shape, meaning that most users have a near-zero troll score. In contrast, the CDF of troll score of trolls in all clusters show a *logarithmic* shape, meaning that most of trolls have a high troll score. However, the CDF of trolls within every cluster have notable differences.

For instance, in Clusters 1 and 2, most trolls are characterized with high troll score (e.g., around only 20% of trolls have a troll score below 0.8) while in Cluster 3, 60% of trolls have a troll score below 0.8. This means that trolls belonging to Cluster 3 have a relatively low troll score, meaning that major part of their trajectories is classified as user trajectories than those of Clusters 1 and 2. We argue that this is due to the fact that trolls of Cluster 3 are very unique among trolls (they represent a small fraction, 5%), and that they are very few (only 20) compared to user accounts that have the same set of visited state-actions pairs (20 times more than the trolls in that cluster). On the contrary, most trolls in Cluster 1, for instance, have high troll scores. We argue that this is due to the fact that our LSTM model identifies specific patterns of activities of the set of visited state-actions of cluster 1 to be linked to troll behavior, as most trolls (75% of trolls) belong to that cluster.

#### 6.4 Identification of Misbehaving (Suspended) Accounts

In this Section, we investigate whether the proposed approach can be effectively used for the identification of generic (i.e., not necessarily troll accounts) misbehaving users, as well as if it can be generalized to a different context (i.e., not necessarily tied with political discussion). Specifically, we evaluate our approach in detecting misbehaving users involved in discussions relative to the Covid-19 virus on Twitter. For this analysis, we used the data set made available by [53], which encompasses tweets that mention specific Covid-19-related keywords. We carried out an hydration

Input Length	AUC	Precision	Recall	TNR	F1-score
100	79.9%	77.36%	73.45%	86.36%	75.24%

Table 4: Account classification results relative to Covid-19 discussion

process through the Twitter API to acquire the whole tweet object from the released tweet IDs [53]. For our evaluations, we considered tweets from February to May 2020, and extracted the list of accounts responsible for those tweets. We then exploited Botometer [54] to filter out bot accounts, and the Twitter API to label the accounts as either active (generic users) or suspended (misbehaving users). Finally, 2,188 active accounts and 446 suspended accounts were left for consideration in our analysis. We generated trajectories considering  $L = 100$ . In total, 5,864 active users’ trajectories and 1,527 suspended users’ trajectories are considered.

By following our approach, we performed a classification of the two classes of accounts, whose results are reported in Table 4. Results show that our approach attains promising performance, with an AUC of 79.9%. Our proposed solution achieves a classification performance of 77%, 73%, and 75%, in terms of precision, recall, and F1-score, respectively. As a preliminary analysis, these results show that our approach has a promising potential in identifying misbehaving accounts. Finally, we observe that our approach attains a TNR of 86%, which suggests that our proposed solution builds a conservative classification model that aims at minimizing the number of misclassified organic users. As the inaccurate classification of organic users might elicit an overhead for social media providers, the conservative nature of our model represents a favorable asset of the proposed methodology.

## 7 Conclusion

In this paper, we focused on the detection of trolls’ activity on Twitter during the 2016 US election. We propose a novel 2-steps approach for the detection of troll accounts. The first step, based on a LSTM neural network, classifies sequences of online activities, modeled in terms of state-action pairs, into either a troll or a user activity. In the second step, we exploit the classified sequences to compute a metric, namely “troll score”, which measures the extent to which an account behaves like a troll. Results show that our approach identifies accounts’ sequences with an AUC of nearly 99% and, accordingly, classifies troll and user accounts with an AUC of 97%, outperforming existing baseline approaches. We then observed the troll score of user and troll accounts. As expected, most trolls have a high troll score (most of their trajectories are classified as troll activity) and that most users show a low troll score (most of their trajectories are classified as user activity). Results also show that some trolls have a low troll score, suggesting that their activity resembles organic users’ behavior. To examine this finding in more detail, we analyzed the activity of trolls and users based on their visited state-action pairs. Our analysis shows that three distinct behavioral clusters separate the various accounts, where every cluster is populated by both trolls and users. Interestingly, trolls of a specific cluster (less populated) have a relatively lower troll score than trolls of other clusters, suggesting that this specific set of trolls behave more similarly to organic users than other trolls. Finally, we tested our approach on a different context with the objective of understanding whether our proposed methodology could be extended to other scenarios. Specifically, we evaluated our approach considering the identification of misbehaving (suspended) users during the Covid-19 discussion on Twitter. Results reveal that, while the nature of suspended users may be similar to that of organic users, our methodology is capable of distinguishing between their activity and producing promising classification results, which will be further validated in our future endeavour.

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