

Online Detection and Infographic Explanation of Spam Reviews with Data Drift Adaptation

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Abstract. Spam reviews are a pervasive problem on online platforms due to its significant impact on reputation. However, research into spam detection in data streams is scarce. Another concern lies in their need for transparency. Consequently, this paper addresses those problems by proposing an online solution for identifying and explaining spam reviews, incorporating data drift adaptation. It integrates (i) incremental profiling, (ii) data drift detection & adaptation, and (iii) identification of spam reviews employing Machine Learning. The explainable mechanism displays a visual and textual prediction explanation in a dashboard. The best results obtained reached up to 87% spam *F*-measure.

Key words: data drift, interpretability and explainability, Natural Language Processing, online machine learning, spam detection.

1. Introduction

Online reviews are a valuable source of information that influences public opinion and directly impacts customers' decision to acquire a product or service (Zhang *et al.*, 2018). However, some reviews are fabricated to promote or undervalue goods and services artificially, i.e. creating spam data (Reyes-Menendez *et al.*, 2019; Hutama and Suhartono, 2022). Spammers can be humans or bots dedicated to creating deceptive reviews (García-Méndez *et al.*, 2022b; Hamida *et al.*, 2022). In this context, spam detection is a critical task in online systems. Spam negatively impacts the user experience and the performance and security of the system (Wang *et al.*, 2021).

Consequently, a broad set of Machine Learning (ML) methods has been explored for spam detection, mainly supervised learning (Crawford *et al.*, 2015). In recent years, Natural Language Processing (NLP) techniques (García-Méndez *et al.*, 2022a) have been

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adopted to improve the accuracy of spam detection (Garg and Girdhar, 2021). Given the dynamic nature of the language and behaviour of spammers, the challenge is maintaining the effectiveness of spam detection over time, integrating the detection of model drifts in a stream-based environment as data and concept drifts (Wang *et al.*, 2019). While data drifts are related to changes in the input data, concept drifts reflect over time in the predicted target (Duckworth *et al.*, 2021). Specifically, concept drifts in spam detection refer to the changes in the statistical properties of the spam and non-spam entries over time, which can cause the spam detection system to misclassify reviews. In addition, in a data stream environment, the distribution of input features used to train the spam detection model can change over time, producing data drifts (Barddal *et al.*, 2017). Notably, the latter drifts are easier to detect and deal with in a transparent model than in an opaque one (Cano and Krawczyk, 2019).

Explainability in spam detection refers to understanding and explaining how a particular text was classified as spam by an automated system (Stites *et al.*, 2021). Therefore, in spam detection, an interpretable mechanism for NLP and concept drift techniques is required to detect spammers in real-time efficiently. According to Crawford *et al.* (2015), the existing data stream spam detection research is scant. Consequently, this paper contributes to an interpretable online spam detection framework that combines NLP techniques and data drift detectors. The proposed framework achieves high accuracy in spam detection and makes the detection process transparent, allowing users to understand why a review is classified as spam. The evaluation with two experimental data sets presents about 85% in the considered evaluation metrics.

The rest of this paper is organized as follows. Section 2 overviews relevant work concerning profiling, classification, data drifts, and explainability for spam detection tasks. Section 3 introduces the proposed method, detailing the data processing, stream-based classification procedures, and online explainability. Section 4 describes the experimental setup and presents the empirical evaluation results considering the online classification and explanation. Finally, Section 5 highlights the achievements and future work.

2. Related Work

As previously mentioned, online reviews have become an essential source of information for consumers to make purchasing decisions (Zhang *et al.*, 2018; Al-Otaibi and Al-Rasheed, 2022). However, spam reviews, which are fake or biased reviews, have become a significant problem, leading to distrust and confusion among consumers (Bian *et al.*, 2021). Accordingly, detecting spam reviews is challenging due to the variety of spamming techniques used by spammers; hence, researchers have proposed various approaches for spam review detection (Wu *et al.*, 2018). These techniques are based on ML methods (Albayati and Altamimi, 2019; Liu *et al.*, 2019; Sun *et al.*, 2022) and social network analysis (Liu *et al.*, 2016; Sun *et al.*, 2022). A representative example of the latter is the work by Rathore *et al.* (2021) on fake reviewer group detection. Their offline graph-based solution, where nodes and edges represent reviewers and products reviewed, respectively,

combines the DeepWalk algorithm with semi-supervised clustering. The authors do not perform textual analysis of the reviews, except sentiment analysis.

Spam detection involves large volumes of data, which can be dynamic and continuously changing (Wang *et al.*, 2019). In the case of data streams, not only are reviews continuously arriving, but their statistical properties may change over time, leading to the concept and data drifts (Karakışli *et al.*, 2019). On the one hand, the volume and speed of online reviews require the adoption of online spam detection techniques (Miller *et al.*, 2014). On the other hand, outcome explainability is crucial for humans to comprehend, trust, and manage the next generation of cyber defense mechanisms such as spam detection (Charmet *et al.*, 2022). Therefore, this related work compares existing works in terms of (i) stream-based profile modelling for spam detection, (ii) stream-based classification mechanisms, and (iii) transparency and credibility in detection tasks.

2.1. Profiling and Classification

Profiling is the process of modelling stakeholders according to their contributions and interactions (Kakar *et al.*, 2021; García-Méndez *et al.*, 2022b). In the case of spam detection, individual profiles are built from the content generated by each stakeholder, humans or bots alike. To overcome information sparsity, the profiles are expected to include side and content information (Faris *et al.*, 2019; Mohawesh *et al.*, 2021), since a richer profile impacts the quality of ML results (Rustam *et al.*, 2021). Mainly, with stream-based modelling, profiles are incrementally updated and refined over time (Veloso *et al.*, 2019, 2020). Concerning online spam detection, the literature considers primary profiling methodologies:

Content-based profiling explores textual features extracted from the text to identify the meaning of the content (Song *et al.*, 2016; Henke *et al.*, 2021; Mohawesh *et al.*, 2021). It can be obtained using linguistic and semantic knowledge or style analysis via NLP approaches.

User-based profiling focuses on both the demographic and the behavioural activity of the user (Miller *et al.*, 2014; Eshraqi *et al.*, 2015; Liu *et al.*, 2016, 2019; Sun *et al.*, 2022). It contemplates demography information, frequency, timing, and content of posts to distinguish legitimate from spammer users. In addition, exploiting the social graph can be relevant since spammers have many followers or friends who are also suspected of being spammers.

Spam detection is a classification task (Vaitkevicius and Marcinkevicius, 2020; Mohawesh *et al.*, 2021). The main classification techniques encompass supervised, semi-supervised, unsupervised, and deep learning approaches (Crawford *et al.*, 2015) and can be applied offline or online. While offline or batch processing builds static models from pre-existing data sets, online or stream-based processing computes incremental models from live data streams (Leal *et al.*, 2021). This paper focuses on stream-based environments. Regarding transparency, classification models can be divided into interpretable and opaque. Opaque mechanisms behave as black boxes (e.g. deep learning), and interpretable

models are self-explainable (e.g. trees- or neighbour-based algorithms) (Carvalho *et al.*, 2019). Interpretable classifiers explain classification outcomes, clarifying why a given content is false or misleading (Škrlić *et al.*, 2021).

2.2. Stream-Based Spam Detection Approaches

Social networking has increased spam activity (Kaur *et al.*, 2018). In this context, spam detection approaches have been explored by social networks (e.g. Twitter,¹ or Facebook²) (Miller *et al.*, 2014; Eshraqi *et al.*, 2015; Liu *et al.*, 2016; Sun *et al.*, 2022), email boxes (Henke *et al.*, 2021), or crowdsourcing platforms (e.g. Wikipedia,³ Yelp,⁴ and TripAdvisor⁵) (Mohawesh *et al.*, 2021). Stream mining became the most effective spam detection approach due to the speed and volume of data. It has been explored in the literature using:

- **Data stream clustering** approaches. Miller *et al.* (2014) treated spam detection as an anomaly prediction problem. The proposed solution identifies spammers on Twitter using account information and streaming tweets employing stream-based clustering algorithms. Eshraqi *et al.* (2015) followed the same methodology, creating clusters of tweets and considering outliers as spam. Song *et al.* (2016) proposed a new ensemble approach named Dynamic Clustering Forest (DCF) for the classification of textual streams, which combines decision trees and clustering algorithms.
- **Data stream classification** for spam detection. Sun *et al.* (2022) proposed a near real-time Twitter spam detection system employing multiple classification algorithms and parallel computing.
- **Outlier detection for stream data.** Liu *et al.* (2019) proposed solution identifies outlier reviews, analyses the differences between the patterns of product reviews, and employs an isolation forest algorithm.

2.2.1. Drifts in Spam Detection

Model drift occurs when the performance of an ML model loses accuracy over time (Ma *et al.*, 2023). The literature identifies two types of drifts: (i) data drifts and (ii) concept drifts. While data drift occurs when the characteristics of the incoming data change, in concept drifts, both input and output distributions present modifications over time (De-sale *et al.*, 2023). According to Gama *et al.* (2014), concept drift detection methods can be divided into three categories: (i) sequential analysis, (ii) statistical analysis, and (iii) sliding windows. In addition, for Lu *et al.* (2018), drift detection involves four stages: (i) data retrieval, (ii) data modelling, (iii) test statistics calculation, and (iv) hypothesis test.

Liu *et al.* (2016) proposed and applied two online drift detection techniques to improve the classification of Twitter spam reviews: (i) fuzzy-based redistribution and (ii)

¹ Available at <https://twitter.com>, May 2024.

² Available at <https://www.facebook.com>, May 2024.

³ Available at <https://es.wikipedia.org>, May 2024.

⁴ Available at <https://yelp.com>, May 2024.

⁵ Available at <https://www.tripadvisor.com>, May 2024.

asymmetric sampling. While the fuzzy-based redistribution technique explores information decomposition, asymmetric sampling balances the size of classes in the training data. Song *et al.* (2016) analysed the distribution of textual information to identify concept drifts in a textual data classification approach. Moreover, Mohawesh *et al.* (2021) employed a comprehensive analysis to address concept drift in detecting fake Yelp reviews. Finally, Henke *et al.* (2021) monitored feature evolution based on the similarity between feature vectors to concept drifts in emails. The solution performs spam classification and concept drift detection as parallel and independent tasks.

In contrast to the previous drift detection works, the current approach adopts self-explainable models to provide explanations, increasing classification quality and user trust.

2.2.2. Explainability

Explainable spam detection refers to explaining why an input was classified as spam. It promotes transparency and clarity, detailing why a particular review was flagged as spam (Stites *et al.*, 2021). Accordingly, interpretable models, such as rule-based systems or decision trees, can explain their reasoning, enhancing trust, reducing bias, and helping to discover additional insights (Rudin, 2019). In addition, NLP enriches the explanations by adding a textual description (Upadhyay *et al.*, 2021). Explainable spam detection has been explored in the literature using Local Interpretable Model Agnostic Explanation (LIME) (Ribeiro *et al.*, 2016) and Shapley Additive Explanations (SHAP) (Reis *et al.*, 2019; Han *et al.*, 2022; Zhang *et al.*, 2022).

The literature shows that existing explainable detectors of fake content in online platforms adopt essentially supervised classification and implement offline processing (Crawford *et al.*, 2015; Henke *et al.*, 2021). Therefore, this paper intends to address this problem by proposing an online solution for identifying and explaining spam reviews, incorporating data drift detection and adaptation.

2.3. Research Contribution

The literature review shows a research gap in detecting data drifts and explaining the classification of textual reviews as spam in real time. In this respect, Rao *et al.* (2021) identifies spam drift detection as a challenge requiring more research. Table 1 provides an overview of the above works considering the data domain, profiling (user- and content-based), spam detection, drift detection, and explainability.

Therefore, this work contributes with an online explainable classification method to recognize spam reviews and, thus, promote trust in digital media. The solution employs data stream processing, updating profiles, and classifying each incoming event. First, user profiles are built using user- and content-based features engineered through NLP. Then, the proposed system monitors the incoming streams to detect data drifts using static and sliding windows. Tree-based classifiers are exploited to obtain an interpretable stream-based classification for classification. Finally, the proposed method provides the user with a dashboard combining visual data and natural language knowledge to explain why an incoming review was classified as spam.

Table 1
Comparison of stream-based spam and drift detection approaches.

Authorship	Domain	Profiling	Spam detection	Drift detection	Explainability
Liu <i>et al.</i> (2016)	Twitter	Content User	Classification (Multiple)	Data	✗
Song <i>et al.</i> (2016)	Spam	Content	Clustering (DT)	Concept	✗
Mohawesh <i>et al.</i> (2021)	Yelp	Content	Classification (LR, PNN, SVM)	Concept	✗
Henke <i>et al.</i> (2021)	Email	Content	Classification (SVM)	Concept	✗
Proposed solution	Yelp	Content User	Classification (DT, RF)	Data	✓

DT – Decision Tree, LR – Logistic Regression, PNN – Perceptron Neural Network, RF – Random Forest, SVM – Support Vector Machine.

As previously explained, concept drift refers to changes in the predicted target over time (i.e. changes in the statistical properties of the spam and non-spam entries), while data drift focuses on input data variations (i.e. changes in the input features used to train the spam detection model). This work focuses on data drift detection, considering its relationship with the transparency of the model. Specifically, detecting data drifts and associated characteristics helps provide richer information to end users via the explainability dashboard. Although no other work has explored the Yelp dataset for data drift and spam detection, work on other topics, such as sentiment analysis, indicates its suitability (Chumakov *et al.*, 2023; Madaan *et al.*, 2023; Wu *et al.*, 2023).

3. Method

The proposed method explores online reviews for stream-based spam classification with drift detection. In addition, it explores self-explainable ML models for transparency. Hence, the data stream classification pipeline, represented in Fig. 1, comprises: (i) feature engineering & incremental profiling (Section 3.1), (ii) feature selection (Section 3.2), (iii) data drift detection & adaptation (Section 3.3), (iv) ML classification (Section 3.4), and (v) explainability (Section 3.5).

3.1. Feature Engineering & Incremental Profiling

The proposed solution processes the content of the reviews with the help of NLP techniques. The content-based features extracted represent relevant linguistic (morphological, syntactical, and semantic) attributes of the reviews. The engineered features are the ratio of adjectives, adverbs, interjections, nouns, pronouns, punctuation marks, verbs, characters, words, difficult words, and URL counters. Moreover, the system also considers the emotional charge of the content (i.e. anger, fear, happiness, sadness, and surprise). The same applies to the polarity charge among negative, neutral, and positive sentiments. More sophisticated linguistic features include readability, using the Flesch readability score, the

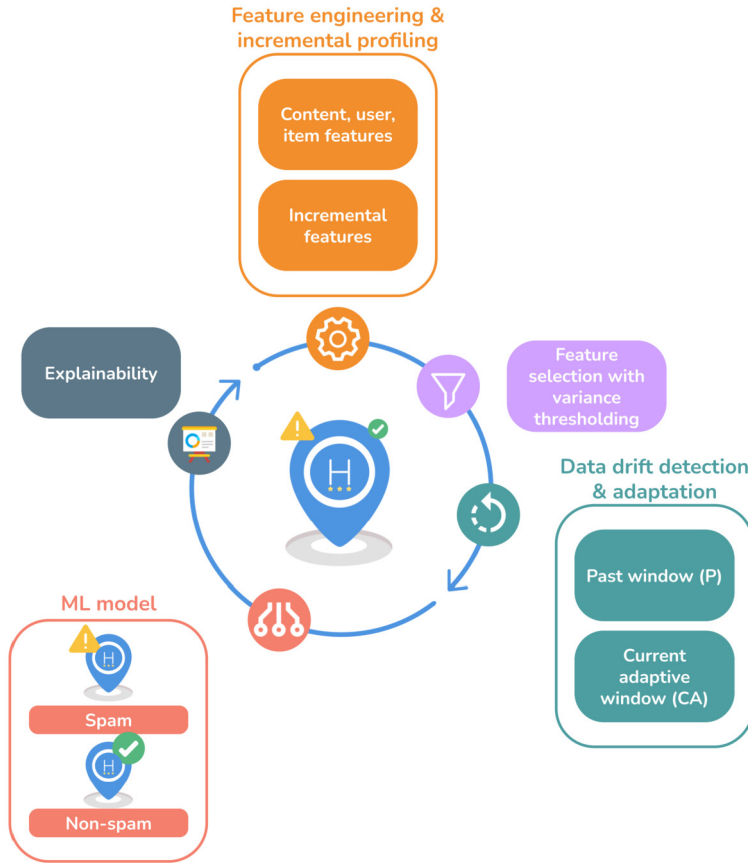


Fig. 1. Data stream classification pipeline.

McAlpine eFLAW score,⁶ and the reading time. In the end, the content itself, i.e. the words, are analysed through word-grams. The char-grams were discarded due to their low scalability in online operation. These content-based features are then used to incrementally build the corresponding user values to update the user profiles. Additionally, incremental relational item features are computed by building a graph of item and user nodes connected by edges containing the corresponding incremental engineered features of the user-reviewed items.

3.2. Feature Selection

Feature selection reduces the feature space dimension by choosing the most relevant features for the classification and contributes to improving the quality of the input data. The adopted selection technique relies on feature variance to discard those with variance lower

⁶A value higher than 25 points is unfavorable.

than a configurable threshold, as suggested by the literature (Engelbrecht *et al.*, 2019; Treisman *et al.*, 2022). In the case of online classification, where the arriving data may evolve with time, the selection of representative features must be performed continuously or periodically.

3.3. Data Drift Detection and Adaptation

The variability of real data over time may affect the performance of ML models, namely the values of evaluation metrics (e.g. accuracy, precision, recovery, etc.). However, the source of the problem may be due to data drifts, concept drifts, ineffective hyper-parameter optimization, and/or class imbalance.

Thus, the proposed system continuously monitors the incoming stream for data drifts and, periodically, under-samples and optimizes the hyperparameters, using two windows: the past (\mathbb{P}) static window and the current adaptive (\mathbb{CA}) sliding window, holding n and w samples, respectively.

The data drift detector starts operating when the cold start ends, and the \mathbb{P} window is initialized with the expected n samples. The detector identifies a data drift whenever: (i) the inter-window word-gram p -value is lower⁷ than 0.05, and (ii) the inter-window *absolute accuracy difference* (\mathbb{AAD}) is higher than 0.05. Algorithm 1 details the data drift detection and adaptation process. The threshold values of 0.05, 0.1, and 0.5 were inspired by the works by Solari *et al.* (2017), Leo and Sardanelli (2020), Ritu Aggrawal (2021), respectively. Figure 2 illustrates this process. The data drift detector works as follows:

- Calculates the word-gram frequency matrices (i.e. the columns represent the word-grams and the rows, the entries) for the \mathbb{P} and \mathbb{CA} windows.
- `Sum_wordgrams` method transforms the latter matrices into vector format (a vector for \mathbb{P} and a vector for \mathbb{CA}) by summing the word-gram frequency for all entries.
- Discards the columns with a frequency lower than 6 in both `sum_wordgrams` vectors.
- Computes the p -value between the word-grams frequency vectors of \mathbb{P} and \mathbb{CA} windows.
- Computes the inter-window \mathbb{AAD} .
- Updates the size of the \mathbb{CA} :
 - If the p -value ≤ 0.1 , the \mathbb{CA} windows size decrements by one.
 - If the p -value > 0.1 and p -value < 0.5 , the \mathbb{CA} windows size remains unchanged.
 - If the p -value ≥ 0.5 , the \mathbb{CA} windows size increments by one.
- Identifies a data drift when the inter-window word-gram p -value is lower (or equal) and the inter-window \mathbb{AAD} is higher (or equal) than 0.05. Then, it replaces the \mathbb{P} with the \mathbb{CA} window and recalculates the optimal hyperparameters. The `hyperparameter_computation` method applies an exhaustive search technique over the configuration parameters listed in Fig. 3. Ultimately, the ML model is trained using the `ml_update` function with the hyperparameters selected and the \mathbb{CA} samples.

⁷In a modern language, the most frequent words in a text are not expected to vary over time, leading to p -values greater than 0.05. However, the contents and the words within spam texts are anticipated to vary over time, resulting in p -values below 0.05.

Algorithm 1 : Data drift detection and classification

```

function MAIN(n,ml_model_name) %n is the configurable cold start threshold, and the name of
the model used (see the list provided in Section 3.4)
    P = [] %Past static window
    CA = [] %Current adaptive sliding window
    list_actual = [] %List with actual values
    list_predicted = [] %List with predicted values
    k = 0 %Sample counter
    system.listener(sample, drift_analysis) %The system waits for the arrival of a new sample to
call the drift analysis function
end function
function DRIFT_ANALYSIS(sample)
    if k < n then %Warm operation
        P.append(sample.wordgrams)
    end if
    CA.append(sample.wordgrams)
    pvalue = 0
    AAD = 0
    k = k + 1
    if k == n then
        accp = accuracy(list_actual, list_predicted)
    end if
    if k ≥ n then
        ca_vector = CA.sum_wordgrams()
        p_vector = P.sum_wordgrams()
        pvalue = chi2(ca_vector, p_vector)
        accca = accuracy(list_actual[-len(CA): ], list_predicted[-len(CA): ])
        AAD = abs(accp - accca)
        if pvalue ≤ 0.1 then
            CA = CA[2: ]
        end if
        if pvalue > 0.1 and pvalue < 0.5 then
            CA = CA[1: ]
        end if
        if pvalue ≤ 0.05 and AAD ≥ 0.05 then
            P = CA
            parametersupdated = hyperparameter_computation(ml_model_name, CA)
            ml_model = ml_update(parametersupdated)
            accp = accuracy(list_actual[-len(P): ], list_predicted[-len(P): ])
        end if
    end if
    predicted, actual = ml_classification_step(ml_model, sample)
    list_actual.append(actual)
    list_predicted.append(predicted)
    sample = input_new_sample()
end function

```

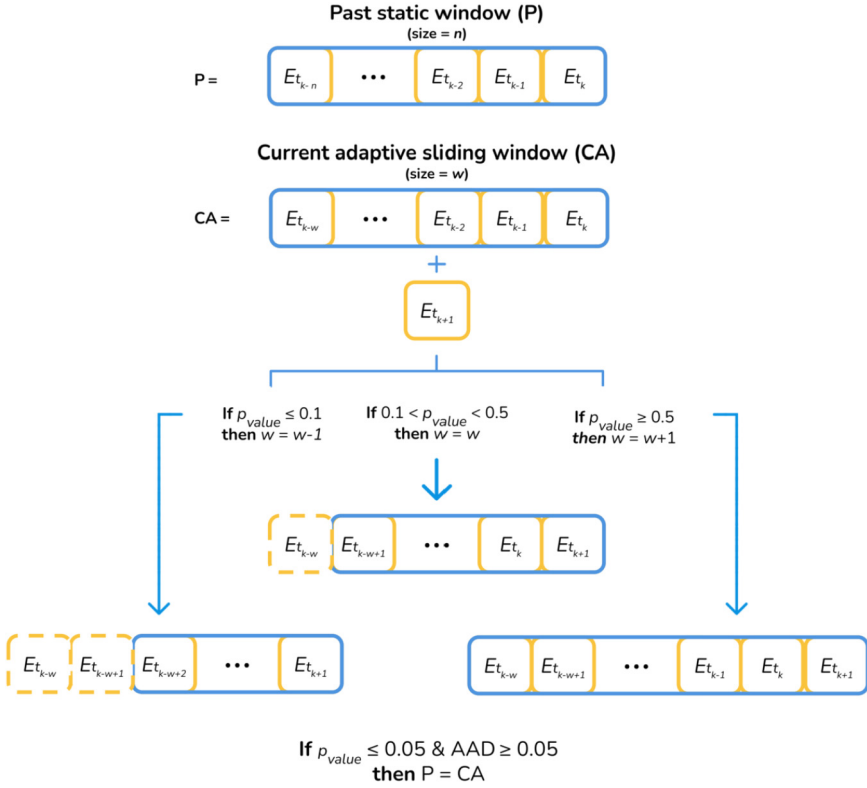


Fig. 2. Data drift detection and adaptation.

3.4. ML Classification

The following online ML algorithms were used as they exhibited good performance in similar classification problems (Liu *et al.*, 2016; Song *et al.*, 2016; Sun *et al.*, 2022).

- **Hoeffding Tree Classifier** (HTC) (Pham *et al.*, 2017) is the basic decision tree model for online learning.
- **Hoeffding Adaptive Tree Classifier** (HATC) (Stirling *et al.*, 2018) monitors branches and replaces them based on their performance.
- **Adaptive Random Forest Classifier** (ARFC) (Gomes *et al.*, 2017) is an ensemble of trees with diversity induction through random re-sampling and concept drift detection. The prediction results are obtained using majority voting.

The algorithmic performance assessment follows the prequential evaluation protocol (Gama *et al.*, 2013) and considers accuracy, macro- and micro-averaging F -measure, and run-time metrics.

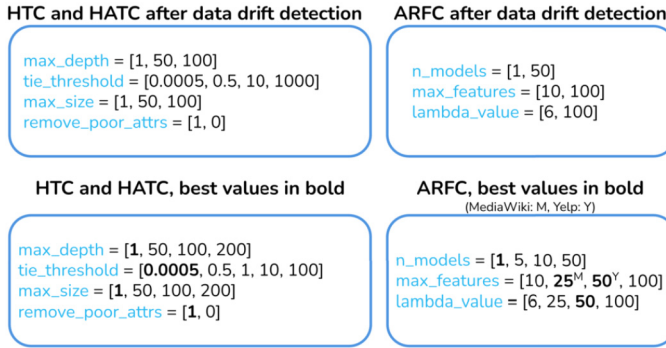


Fig. 3. Model hyperparameter configuration (best values in bold).

3.5. Explainability

This module provides information about the most relevant features for the classification, i.e. those with a frequency of appearance greater than a configurable threshold. This information is extracted from the estimators of the tree models used (see Fig. 3): HTC single-model estimator (Pham *et al.*, 2017), HATC single-model estimator (Stirling *et al.*, 2018) and ARFC multi-model estimator (Gomes *et al.*, 2017). The predictions regarding the most relevant features and data drift detection are described in natural language. Furthermore, the decision tree path followed is also provided, along with an automatic description obtained from a Large Language Model.

4. Experimental Results

This section describes the experimental data set (Section 4.1) and the implementation of the different modules⁸: (i) feature engineering & incremental profiling (Section 4.2), (ii) feature selection (Section 4.3), and (iii) data drift detection & adaptation (Section 4.4). The classification and explainability results are detailed in Section 4.5 and Section 4.6, respectively.

The experiments contemplate four stream classification scenarios, incorporating feature selection, hyperparameter optimization⁹ and incremental accuracy updating.

Scenario 1. The data stream classification runs on a single processing thread.

Scenario 2. The data stream classification runs on a range of 10–20 parallel threads based on the workload to reduce the experimental run-time. To preserve the original data distribution, the chronologically ordered data stream was divided into consecutive sub-streams, and then, each sub-stream was processed in a dedicated thread.

Scenario 3. The data stream classification includes data drift detection & adaptation and runs according to scenario 2.

⁸Code available at https://github.com/nlpgti/data_drift

⁹Hyper-parameter optimization was performed with the 0.005% of the experimental samples in Section 4.5.

Table 2
Distribution of classes in the experimental data sets.

Data set	Class	Number of entries
Yelp	Spam	36885
	Non-spam	322167
	Total	359052
MediaWiki	Spam	24877
	Non-spam	294979
	Total	319856

Scenario 4. The data stream classification runs on a single processing thread with data drift detection & adaptation.¹⁰

All experiments were performed using a server with the following hardware specifications:

- **Operating System:** Ubuntu 18.04.2 LTS 64 bits
- **Processor:** IntelCore i9-10900K 2.80GHz
- **RAM:** 96 GB DDR4
- **Disk:** 480 GB NVME + 500 GB SSD

4.1. Experimental Data Set

The Yelp data set¹¹ is composed of 359 052 leisure activity entries between October 2004 and January 2015, distributed between 36 885 and 322 167 samples of spam and non-spam content, respectively (see Table 2). Moreover, the MediaWiki data set¹² contains contributions to travel wikis between August 2003 and June 2020. It is composed of 319 856 entries, distributed between 24 877 and 249 979 samples of spam and non-spam content, respectively (see Table 2).

4.2. Feature Engineering & Incremental Profiling

This section details the implementations and NLP techniques used to create the classification features. Table 3, Table 4, and Table 5 detail the content features, the incremental user features, and the incremental item features for Yelp and MediaWiki data sets, respectively.

Most ratio and counter features in Table 3 (features 1, 2, 7, 9, 11, 12, 15 in Table 3) are computed using the spaCy¹³ tool to gather their grammatical category (`token.pos_` feature). The character and word count (features 3 and 16, respectively) have been directly calculated with the Python `len` function.¹⁴ The URL count (feature 14) was computed us-

¹⁰Due to time limitations, this scenario will only be applied with the best classifier so far.

¹¹Available at <https://www.kaggle.com/datasets/abidmeera/yelp-labelled-dataset?select=Labelled+Yelp+Dataset.csv>, May 2024.

¹²Available from the corresponding author on reasonable request.

¹³Available at <https://spacy.io>, May 2024.

¹⁴For feature 16, the text was first separated into word tokens.

Table 3
Content-based features explored per experimental data set.

Data set	ID	Name	Description	Type
Common	1	Adjective ratio	Ratio of adjectives in the content	Engineerd (Eng.)
	2	Adverb ratio	Ratio of adverbs in the content	
	3	Character count	Number of characters in the content	
	4	Difficult word count	Number of the difficult words in the content	
	5	Emotion (anger, fear, happiness, sadness, surprise)	Load of the different emotions in the content	
	6	Flesch readability	Readability score of the content	
	7	Interjection ratio	Ratio of interjections in the content	
	8	McAlpine EFLAW readability	Readability score of the content for non-native English speakers	
	9	Noun ratio	Ratio of nouns in the content	
	10	Polarity	Sentiment of the content	
	11	Pronoun ratio	Ratio of pronouns in the content	
	12	Punctuation ratio	Ratio of punctuation marks in the content	
	13	Reading time	Content reading time	
	14	URL count	Number of URL in the content	
	15	Verb ratio	Ratio of verbs in the content	
	16	Word count	Number of words in the content	
	17	Word n -grams	Single and bi-words grams	
Yelp	18	Rating-polarity deviation	Rating deviation concerning the polarity of the content	Eng.
	19	Review rating	Rating of the review	Raw
MediWiki	20	Bot flag	The user is a bot	Raw
	21	Deleted flag	Part of the revision content is hidden	
	22	New flag	It is the first revision of a page	
	23	Revert flag	The revision was reverted	
	24	Size difference	Difference in the number of characters added and deleted in the revision	
	25	Edit quality	False/true damaging & good faith probability	
	26	Item quality	A, B, C, D, E probability	
27	Article quality	OK, attack, vandalism, WP1OB, WP1OC, WP1OFA, WP1OGA, WP1OSTART, WP1OSTUB probability		

ing a regular expression.¹⁵ The emotion (feature 5) and polarity (feature 10) are calculated using `Text2emotion`¹⁶ and `TextBlob`,¹⁷ respectively. The rating-polarity deviation is computed as the difference between those values after moving the polarity to a Likert scale¹⁸ (feature 18). The system uses `Textstat`¹⁹ for the readability (features 4, 6 and 8) and reading time (feature 13). Word-grams (single and bi-words, feature 17) are obtained with `CountVectorizer`²⁰ with the `HATC` model as the meta-transformer, and using

¹⁵Available at <https://bit.ly/3N4GNM3>, May 2024.

¹⁶Values between 0 and 1. Available at <https://pypi.org/project/text2emotion>, May 2024.

¹⁷Values between -1 and 1. Available at <https://pypi.org/project/spacytextblob>, May 2024.

¹⁸ $\text{Polarity_likert} = 2.5 * (\text{polarity} + 1)$.

¹⁹Available at <https://pypi.org/project/textstat>, May 2024.

²⁰Available at https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.CountVectorizer.html, May 2024.

Table 4
User engineered features for both experimental data sets.

ID	Name	Description
{28, 81}	User features	Incremental average and maximum per user regarding features 1 to 27 in Table 3.
82	User post count	Cumulative number of posts per user.
83	User spam tendency	Known spamming behaviour per user.
84	User posting antiquity	Posting antiquity per user (in weeks).
85	User posting frequency	Weekly posting frequency per user.

Table 5
Item engineered features for both experimental data sets.

ID	Name	Description
{86, 139}	Item features	Incremental average and maximum per item regarding features 1 to 27 in Table 3.
{140, 177}	Item and rating features	Incremental average and maximum per item and rating regarding features 1 to 19 in Table 3.

the following parameters: $\max_df=0.7$, $\min_df=0.1$.²¹ For the word-grams generation, the review is pre-processed, removing non-textual characters (numbers, punctuation marks, and subsequent blank spaces), stop words,²² and URL instances. Then, the review text is lemmatized with spaCy using the `en_core_web_md` model.²³ The drift detector exclusively uses the inter-window word-grams *p-value* variations.

Table 4 and Table 5 summarize the user incremental features (58 features) and item incremental features (92 features) generated from the content-based features in Table 3. The user engineered features of Table 4 and Table 5 correspond to the incremental average $f_{avg_{t_k}}$ given by equation (1) and the incremental maximum $f_{max_{t_k}}$ given by equation (2), where f represents the feature and $[f_{t_0}, f_{t_1}, \dots, f_{t_k}]$ the past feature data per user.

$$f_{avg_{t_k}} = \frac{\sum_{i=0}^k f_{t_i}}{k}, \quad (1)$$

$$f_{max_{t_k}} = \max_i f_{t_i}. \quad (2)$$

4.3. Feature Selection

To reduce the feature space dimension, the variance of the features in Table 3 and Table 4 is analysed with the help of the `VarianceThreshold`²⁴ from River 0.11.1.²⁵ The

²¹For the MediaWiki data set, $\min_df=0.01$ since the reviews are shorter.

²²Available at <https://gist.github.com/sebleier/554280>, May 2024.

²³Available at <https://spacy.io/models/en>, May 2024.

²⁴Available at <https://riverml.xyz/0.11.1/api/feature-selection/VarianceThreshold>, May 2024.

²⁵Available at <https://riverml.xyz/0.11.1>, May 2024.

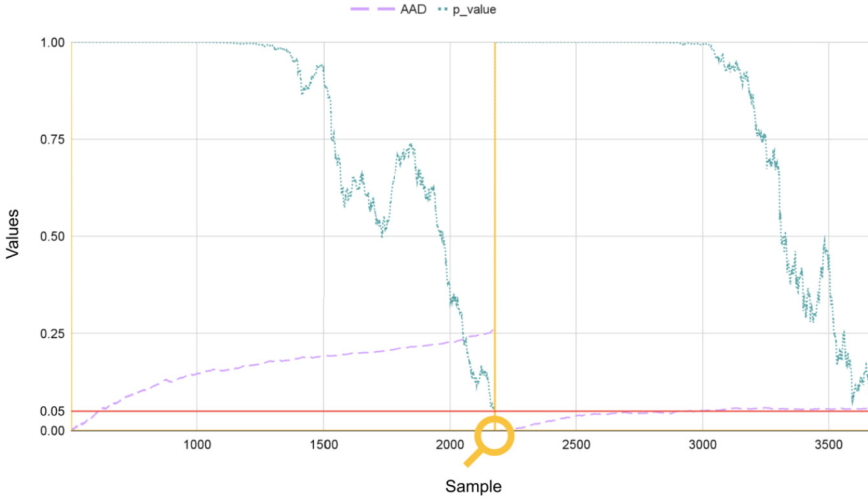


Fig. 4. Data drift detection & adaptation based on inter-window AAD and word-gram p -value.

threshold is set to 0, the default value. In the case of Yelp, only feature 14 in Table 3 and its incremental versions in Table 4 and Table 5 were discarded. The discarded MediaWiki features include features 21 and 22 in Table 3 and their incremental versions in Table 4 and Table 5, along with the incremental version of feature 20 in Table 4. All remaining features passed the threshold and were, thus, considered relevant for the classification.

4.4. Data Drift Detection and Adaptation

While standard online ML models can adapt to data changes over time, they are still affected by data drift, also known as covariate shift. To address this issue, scenario 3 incorporates data drift detection & adaptation. Moreover, it defines that: (i) the cold start spans over the first 500 samples, corresponding to the initial width of the p window; (ii) the maximum width of c_A sliding windows is 2000 samples. The proposed data drift detector determines the inter-window word-gram p -value and the inter-window AAD , using the `Chi2ContingencyResult` function²⁶ and the `accuracy_score` function,²⁷ respectively.

Figure 4 shows the evolution of the inter-window AAD and word-gram p -value. The lens marks the detected data drift when p -value drops to 0.05, and AAD is above 0.05.

Once a drift is identified, the hyperparameter optimization starts. This process, which is the most time demanding, employs `GridSearch`²⁸ with reduced configuration parameters (see Fig. 3).

²⁶ Available at https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.chi2_contingency.html, May 2024.

²⁷ Available at https://scikit-learn.org/stable/modules/generated/sklearn.metrics.accuracy_score.html, May 2024.

²⁸ Available at https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html, May 2024.

Table 6
Online spam prediction results (best values in bold) for the Yelp data set.

Scenario	Model	Accuracy	F-measure			Time (s)
			Macro	Non-spam	Spam	
1	HTC	61.22	54.48	72.00	36.96	29.20
	HATC	61.42	55.07	71.96	38.18	32.26
	ARFC	65.96	65.96	66.13	65.78	205.45
2	HTC	62.51	57.99	71.77	44.21	5.07
	HATC	62.17	57.70	71.44	43.97	6.39
	ARFC	60.76	60.75	60.99	60.52	19.93
3	HTC	67.88	67.06	72.26	61.87	287.50
	HATC	69.57	69.55	70.26	68.84	515.32
	ARFC	75.82	75.55	73.00	78.10	2346.75
4	ARFC	78.75	78.44	75.85	81.03	9678.32

4.5. ML Classification

The selected classification techniques include HTC,²⁹ HATC,³⁰ and ARFC³¹ from River 0.11.1.³²

Figure 3 details all hyperparameter optimization values. Their ranges and best values were defined experimentally. Identifying the best values relied on an *ad hoc* implementation of GridSearch for data streams.

As the solution operates in streaming mode, no retraining is needed. However, the model’s performance is expected to be lower during cold start (initial samples) or with tiny data streams. Consequently, this solution is intended for domains continuously producing large volumes of textual data.

Summing up, the results in Tables 6, 7 and 8 are estimated with an *ad hoc* implementation of the `progressive_val_score`³³ from River 0.11.1. Moreover, the validation scheme comprises prediction and training steps as the system operates in streaming. Consequently, the results displayed correspond to the last computation with the last incoming sample, that is, the last chronologically ordered sample.

Table 6 shows the results obtained in the spam versus non-spam review classification in the four scenarios with the Yelp data set.

In scenarios 1 and 2, the values approach the 60% threshold for all models. Unfortunately, the spam *F*-measure in scenario 1 does not reach the 40% in HTC and HATC. Scenarios 1 and 2 display the same accuracy results since they only differ on the number of running threads. Nonetheless, scenario 3 presents a remarkable improvement in the spam *F*-measure (+30.66 percentage points for HATC). Scenario 3, with data drift de-

²⁹ Available at <https://riverml.xyz/0.11.1/api/tree/HoeffdingTreeClassifier>, May 2024.

³⁰ Available at <https://riverml.xyz/0.11.1/api/tree/HoeffdingAdaptiveTreeClassifier>, May 2024.

³¹ Available at <https://riverml.xyz/0.11.1/api/ensemble/AdaptiveRandomForestClassifier>, May 2024.

³² Due to computational and time constraints, results were obtained with a balanced subset composed of 73 770 and 49 754 samples for the Yelp and MediaWiki data sets, respectively.

³³ Available at <https://riverml.xyz/0.11.1/api/evaluate/progressive-val-score>, May 2024.

Table 7
Online spam prediction results (best values in bold) for the MediaWiki data set.

Scenario	Model	Accuracy	F-measure			Time (s)
			Macro	Non-spam	Spam	
1	HTC	80.78	80.05	76.23	83.87	18.64
	HATC	80.75	80.02	76.20	83.84	21.28
	ARFC	71.15	71.11	72.18	70.03	65.21
2	HTC	79.65	78.95	75.10	82.79	4.40
	HATC	79.84	79.16	75.40	82.92	5.02
	ARFC	69.75	69.72	70.68	68.76	9.91
3	HTC	81.78	81.46	79.03	83.89	373.73
	HATC	82.23	82.00	79.97	84.03	510.45
	ARFC	84.03	83.80	81.84	85.75	2333.31
4	ARFC	86.13	85.89	84.02	87.75	5817.78

tection & adaptation, reaches a spam F -measure of 78.10% and an average run-time per sample of 32 ms with the ARFC model, detecting an average of 1.75 drifts per thread (35 data drifts in total). This indicates that data drift detection & adaptation contributes to increasing the spam classification accuracy (+17.58 percentage points in F -measure) and that multi-threading with 20 threads can process an average of 31 sample/s. Finally, scenario 4 exploits ARFC, the best-performing model in scenarios 1, 2, and 3, with data drift detection & adaptation on a single processing thread. It presents top values for all metrics, including an 81.03% in spam F -measure and an average run-time per sample of 130 ms. This last scenario was able to detect 14 drifts and process 8 sample/s. The difference in the number of data drifts detected in scenario 3 (35) and scenario 4 (14) is caused by thread cold start, i.e. each one of the 20 threads starts with a void model.

Table 7 shows the evaluation with the MediaWiki data set. The low results of scenario 2, caused by parallelization, improve in scenario 3 thanks to data drift detection & adaptation. The promising performance of ARFC is further enhanced in scenario 4 with a notable increase in the non-spam F -measure between scenario 1 and 4 (+11.84 percentage points). All evaluation metrics are around 85%. The number of data drifts and sample processing rate are similar to those obtained with the Yelp data set. In scenario 3, the ARFC model reports an average run-time per sample of 47 ms (21 sample/s) and 38 data drifts (3.8 drifts per thread). The ML model in scenario 4 has identified 10 data drifts and processed 116 ms/sample.

The appropriateness of the proposed drift detection algorithm is supported by its comparison with the Early Drift Detection Method (EDDM)³⁴ and ADaptive WINDOWing (ADWIN)³⁵ drift detectors. Table 8 shows the results of the ARFC model in scenario 4 with the three drift detectors and the selected experimental data sets. The proposed drift detector attains the best results followed by ADWIN (23.24 percent points lower in the F -measure for the spam class). Moreover, EDDM detects many drifts (793 and 161 for the

³⁴ Available at <https://riverml.xyz/0.11.1/api/drift/EDDM>, May 2024.

³⁵ Available at <https://riverml.xyz/0.11.1/api/drift/ADWIN>, May 2024.

Table 8
 Online spam prediction results in scenario 4 with different drift detectors (best values in bold).

Data set	Drift detector	Accuracy	F-measure			Time (s)
			Macro	Non-spam	Spam	
Yelp	EDDM	54.58	54.58	54.53	54.63	373.37
	ADWIN	60.56	60.56	60.70	60.42	363.12
	Proposed	78.75	78.44	75.85	81.03	9678.32
MediaWiki	EDDM	62.70	62.70	63.22	62.17	1078.25
	ADWIN	65.09	65.08	65.65	64.51	1178.08
	Proposed	86.13	85.89	84.02	87.75	5817.78

Yelp and MediaWiki data sets, respectively), which increases the number of training sessions, negatively affecting performance. ADWIN identifies a few drifts in the Yelp data set (i.e. 6) and a higher number in the MediaWiki data set (38).

Analysis of these spam detection results against those of related works found in the literature with the Yelp data set is merely indicative, as it compares the performance of incremental online versus offline classification methods. Nevertheless, the current method outperforms the 62.35% accuracy reported by Mohawesh *et al.* (2021) by 16.4 percent points in the Yelp NYC data set with 322 167 reviews. Furthermore, the values obtained with the ADWIN concept drift detection technique by Mohawesh *et al.* (2021) are aligned with those reported in Table 8. This helps to validate the current method, which attains superior performance. Unfortunately, no information is provided for the specific case of the spam class (i.e. micro-averaging evaluation), in which the current incremental method surpasses the 80% barrier in F-measure. Moreover, Mohawesh *et al.* (2021) focused on concept rather than data drift and did not include explainability capabilities, a distinctive feature of the current method.

4.6. Explainability

Figure 5 displays the graphical and textual explanation of the classification of an incoming review. The buttons on the left vertical bar enable: (i) administrator profile access, (ii) search reviews by textual content, (iii) search reviews by timestamp, (iv) access to alerts, (v) visualization of the decision tree and associated natural language description (see Fig. 6), (vi) saving the results in the cloud, and (vii) configuring the colour layout (i.e. dark or clear mode). The most representative features for the classification are shown in the top part. The relevance of the features corresponds to their frequency of appearance in the decision tree path, considering only positive (greater than) bifurcations (see the graph in Fig. 6). The white feature navigation panel on the top right displays the most relevant features. The coloured circle that accompanies this drop-down menu represents the level of severity (i.e. green when the value is higher than the 50th user quartile, yellow if the feature value is within the 50th–25th range, and red when it is lower than the 25th user quartile). While these selectors only apply to the coloured cards on the left, the review panel on the bottom affects the whole dashboard and enables the analysis of different reviews (i.e. using the previous and next buttons). Finally, there are two additional buttons



Fig. 5. Explainability dashboard (relevant features).

for feedback (i.e. to indicate whether the prediction is correct or not). This allows a manager to provide feedback, acting as an expert in the loop. The displayed review exhibits a high charge of anger and a significant deviation between the user rating and the detected polarity, the editor has been associated with spam content in the past, and the sample has been classified as spam with a 75% confidence using the `Predict_Proba_One` function³⁶ from River 0.11.1.

Finally, the system presents the decision tree path of the prediction and the corresponding natural language description obtained with GPT3³⁷ (see Fig. 6). GPT3 was configured to use the `text-davinci-003` model with the default parameters, except the `temperature` parameter, which was set to 0.7, to generate human-like natural language descriptions. At the top, the administrator can navigate the different decision trees using the previous and next buttons, with the decision path highlighted in blue.

5. Conclusion

The use of crowdsourcing platforms to get information about products and services is growing. Customers search for reviews to make the best decision. Individuals submit dishonest and misleading feedback to manipulate a product or service's reputation or perception. These spam reviews can be created for various reasons, including financial gain, personal grudges, or competitive advantage. To address this problem, the proposed online method identifies and explains spam reviews. In addition, this research contributes with an

³⁶ Available at <https://riverml.xyz/0.11.1/api/base/Classifier>, May 2024.

³⁷ Available at <https://openai.com/product>, May 2024.

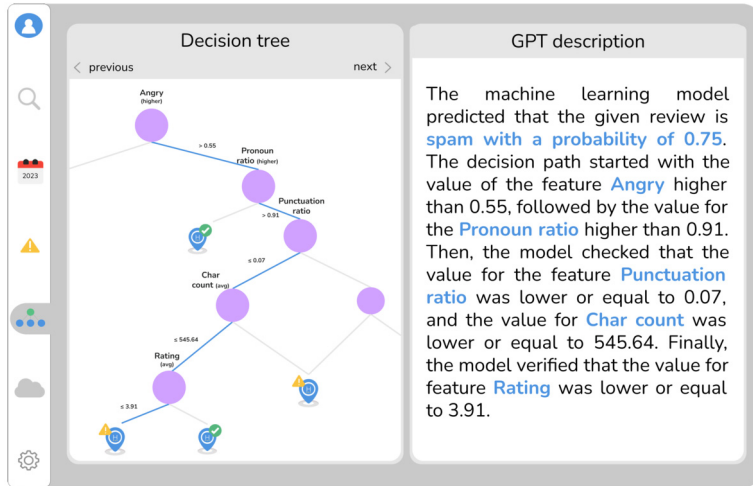


Fig. 6. Explainability dashboard (decision path and Large Language Model description).

online explainable classification engine to recognize spam reviews and, thus, to promote trust in digital media.

Specifically, the proposed method comprises (i) stream-based data processing (through feature engineering, incremental profiling, and selection), (ii) data drift detection & adaptation, (iii) stream-based classification, and (iv) explainability. The solution relies on stream-based processing, incrementally updating the profiling and classification models on each incoming event. Specifically, user profiles are computed using user- and content-based features engineered through NLP. Monitoring the incoming streams, the method detects data drifts using static and sliding windows. The classification relies on tree-based classifiers to obtain an interpretable stream-based classification. As a result, the user dashboard includes visual data and natural language knowledge to explain the classification of each incoming event. The experimental classification results of the proposed explainable and stream-based spam detection method show promising performance: 78.75% accuracy and 78.44% macro F -measure obtained with the Yelp data set, and 86.13% accuracy and 85.89% macro F -measure with the MediaWiki data set. Moreover, the proposed data drift detection & adaptation approach performs better than well-known drift detectors (23.24 percent points higher in the F -measure for spam detection). According to the related work analysis, this proposal is the first to jointly provide stream-based data processing, profiling, classification with data drift detection & adaptation, and explainability.

This solution can be extended to detect orchestrated groups of active spammers thanks to its modular design with NLP techniques and *ad hoc* clustering methods for streaming operation. To this end, additional side and content features can be incorporated to cluster contributors by location and temporal affinity. New content-based features can be explored to represent the semantic (e.g. ontology-based like WordNet Domains) and non-semantic similarity (e.g. cosine distance) between reviews. In this regard, the current version of the system already considers sentiment and emotion analysis. The corresponding incremental

features can then be designed per user and group of closely related users. The system should, therefore, be able to dynamically adapt to changes in the spamming behaviour of both individuals and groups. Moreover, in future work, the online processing throughput can be further improved by adopting parallelization algorithms, which explore the intrinsic distribution of the data together with elastic hardware solutions. Considering the online processing of reviews, the number of threads and the allocation of incoming samples to threads can be location-based, e.g. employing separate dedicated threads to process the reviews of New York, London, or Paris.

Authors' Contributions

Francisco de Arriba-Pérez: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing – Original Draft, Writing – Review & Editing, Visualization, Project Administration, Funding Acquisition. **Silvia García-Méndez:** Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing – Original Draft, Writing – Review & Editing, Visualization, Project Administration, Funding Acquisition. **Fátima Leal:** Conceptualization, Resources, Writing – Original Draft. **Benedita Malheiro:** Conceptualization, Methodology, Validation, Writing – Review & Editing, Supervision. **Juan Carlos Burguillo-Rial:** Conceptualization, Writing – Review & Editing.

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References

- Al-Otaibi, S.T., Al-Rasheed, A.A. (2022). A review and comparative analysis of sentiment analysis techniques. *Informatica*, 46(6), 33–44. <https://doi.org/10.31449/inf.v46i6.3991>.
- Albayati, M.B., Altamimi, A.M. (2019). An empirical study for detecting fake facebook profiles using supervised mining techniques. *Informatica*, 43(1), 77–86. <https://doi.org/10.31449/inf.v43i1.2319>.
- Barddal, J.P., Gomes, H.M., Enembreck, F., Pfahringer, B. (2017). A survey on feature drift adaptation: definition, benchmark, challenges and future directions. *Journal of Systems and Software*, 127, 278–294. <https://doi.org/10.1016/j.jss.2016.07.005>.
- Bian, P., Liu, L., Sweetser, P. (2021). Detecting spam game reviews on steam with a semi-supervised approach. In: *Proceedings of the International Conference on the Foundations of Digital Games*. Association for Computing Machinery, pp. 1–10. 9781450384223. <https://doi.org/10.1145/3472538.3472547>.
- Cano, A., Krawczyk, B. (2019). Evolving rule-based classifiers with genetic programming on GPUs for drifting data streams. *Pattern Recognition*, 87, 248–268. <https://doi.org/10.1016/j.patcog.2018.10.024>.
- Carvalho, D.V., Pereira, E.M., Cardoso, J.S. (2019). Machine learning interpretability: a survey on methods and metrics. *Electronics*, 8(8), 832. <https://doi.org/10.3390/electronics8080832>.

- Charmet, F., Tanuwidjaja, H.C., Ayoubi, S., Gimenez, P.F., Han, Y., Jmila, H., Blanc, G., Takahashi, T., Zhang, Z. (2022). Explainable artificial intelligence for cybersecurity: a literature survey. *Annals of Telecommunications*, 77, 789–812. <https://doi.org/10.1007/s12243-022-00926-7>.
- Chumakov, S., Kovantsev, A., Surikov, A. (2023). Generative approach to aspect based sentiment analysis with GPT language models. *Procedia Computer Science*, 229, 284–293. <https://doi.org/10.1016/j.procs.2023.12.030>.
- Crawford, M., Khoshgoftaar, T.M., Prusa, J.D., Richter, A.N., Al Najada, H. (2015). Survey of review spam detection using machine learning techniques. *Journal of Big Data*, 2(1), 1–24. <https://doi.org/10.1186/s40537-015-0029-9>.
- Desale, K.S., Shinde, S., Magar, N., Kullolli, S., Kurhade, A. (2023). Fake review detection with concept drift in the data: a survey. In: *Proceedings of International Congress on Information and Communication Technology*, Vol. 448. Springer, pp. 719–726. 9789811916090. https://doi.org/10.1007/978-981-19-1610-6_63.
- Duckworth, C., Chmiel, F.P., Burns, D.K., Zlatev, Z.D., White, N.M., Daniels, T.W.V., Kiuber, M., Boniface, M.J. (2021). Using explainable machine learning to characterise data drift and detect emergent health risks for emergency department admissions during COVID-19. *Scientific Reports*, 11, 23017–23026. <https://doi.org/10.1038/s41598-021-02481-y>.
- Engelbrecht, A.P., Grobler, J., Langeveld, J. (2019). Set based particle swarm optimization for the feature selection problem. *Engineering Applications of Artificial Intelligence*, 85, 324–336. <https://doi.org/10.1016/j.engappai.2019.06.008>.
- Eshraqi, N., Jalali, M., Moattar, M.H. (2015). Detecting spam tweets in Twitter using a data stream clustering algorithm. In: *Proceedings of the International Congress on Technology, Communication and Knowledge*. IEEE, pp. 347–351. 978-1-4673-9762-9. <https://doi.org/10.1109/ICTCK.2015.7582694>.
- Faris, H., Al-Zoubi, A.M., Heidari, A.A., Aljarah, I., Mafarja, M., Hassonah, M.A., Fujita, H. (2019). An intelligent system for spam detection and identification of the most relevant features based on evolutionary Random Weight Networks. *Information Fusion*, 48, 67–83. <https://doi.org/10.1016/j.inffus.2018.08.002>.
- Gama, J., Sebastião, R., Rodrigues, P.P. (2013). On evaluating stream learning algorithms. *Machine Learning*, 90(3), 317–346. <https://doi.org/10.1007/s10994-012-5320-9>.
- Gama, J., Žliobaitė, I., Bifet, A., Pechenizkiy, M., Bouchachia, A. (2014). A survey on concept drift adaptation. *ACM Computing Surveys*, 46(4), 44–80. <https://doi.org/10.1145/2523813>.
- García-Méndez, S., de Arriba-Pérez, F., Barros-Vila, A., González-Castaño, F.J. (2022a). Detection of temporality at discourse level on financial news by combining Natural Language Processing and Machine Learning. *Expert Systems with Applications*, 197(1), 116648–116656. <https://doi.org/10.1016/j.eswa.2022.116648>.
- García-Méndez, S., Leal, F., Malheiro, B., Burguillo-Rial, J.C., Veloso, B., Chis, A.E., González-Vélez, H. (2022b). Simulation, modelling and classification of wiki contributors: Spotting the good, the bad, and the ugly. *Simulation Modelling Practice and Theory*, 120, 102616–102628. <https://doi.org/10.1016/j.simpat.2022.102616>.
- Garg, P., Girdhar, N. (2021). A systematic review on spam filtering techniques based on natural language processing framework. In: *Proceedings of the International Conference on Cloud Computing, Data Science & Engineering*. IEEE, pp. 30–35. <https://doi.org/10.1109/Confluence51648.2021.9377042>.
- Gomes, H.M., Bifet, A., Read, J., Barddal, J.P., Enembreck, F., Pfharinger, B., Holmes, G., Abdessalem, T. (2017). Adaptive random forests for evolving data stream classification. *Machine Learning*, 106(9–10), 1469–1495. <https://doi.org/10.1007/s10994-017-5642-8>.
- Hamida, Z.F., Refouf, A., Drif, A., Giordano, S. (2022). Hybrid-MELAu: a hybrid mixing engineered linguistic features based on autoencoder for social bot detection. *Informatica*, 46(6), 143–158. <https://doi.org/10.31449/inf.v46i6.4081>.
- Han, S., Wang, H., Li, W., Zhang, H., Zhuang, L. (2022). Explainable knowledge integrated sequence model for detecting fake online reviews. *Applied Intelligence*, 53, 6953–6965. <https://doi.org/10.1007/s10489-022-03822-8>.
- Henke, M., Santos, E., Souto, E., Santin, A.O. (2021). Spam detection based on feature evolution to deal with concept drift. *Journal of Universal Computer Science*, 27, 364–386. <https://doi.org/10.3897/jucs.66284>.
- Hutama, L.B., Suhartono, D. (2022). Indonesian hoax news classification with multilingual transformer model and BERTopic. *Informatica*, 46(8), 81–90. <https://doi.org/10.31449/inf.v46i8.4336>.
- Kakar, S., Dhaka, D., Mehrotra, M. (2021). Value-based retweet prediction on twitter. *Informatica*, 45, 267–276. <https://doi.org/10.31449/inf.v45i2.3465>.

- Karakaşlı, M.S., Aydin, M.A., Yarkan, S., Boyacı, A. (2019). Dynamic feature selection for spam detection in twitter. In: *Lecture Notes in Electrical Engineering*, Vol. 504. Springer, pp. 239–250. https://doi.org/10.1007/978-981-13-0408-8_20.
- Kaur, R., Singh, S., Kumar, H. (2018). Rise of spam and compromised accounts in online social networks: a state-of-the-art review of different combating approaches. *Journal of Network and Computer Applications*, 112, 53–88. <https://doi.org/10.1016/j.jnca.2018.03.015>.
- Leal, F., Veloso, B., Malheiro, B., Burguillo, J.C. (2021). Crowdsourced data stream mining for tourism recommendation. In: *Advances in Intelligent Systems and Computing*, vol. 1365 AIST. Springer, pp. 260–269. https://doi.org/10.1007/978-3-030-72657-7_25.
- Leo, G.D., Sardaneli, F. (2020). Statistical significance: p value, 0.05 threshold, and applications to radiomics—reasons for a conservative approach. *Euro Radiology Experimental*, 4, 1–8. <https://doi.org/10.1186/s41747-020-0145-y>.
- Liu, S., Zhang, J., Xiang, Y. (2016). Statistical detection of online drifting twitter spam: invited paper. In: *Proceedings of the Asia Conference on Computer and Communications Security*. Association for Computational Linguistics, pp. 1–10. 9781450342339. <https://doi.org/10.1145/2897845.2897928>.
- Liu, W., He, J., Han, S., Cai, F., Yang, Z., Zhu, N. (2019). A method for the detection of fake reviews based on temporal features of reviews and comments. *IEEE Engineering Management Review*, 47, 67–79. <https://doi.org/10.1109/EMR.2019.2928964>.
- Lu, J., Liu, A., Dong, F., Gu, F., Gama, J., Zhang, G. (2018). Learning under concept drift: a review. *IEEE Transactions on Knowledge and Data Engineering*, 31(12), 2346–2363. <https://doi.org/10.1109/TKDE.2018.2876857>.
- Ma, T., Wang, X., Zhou, F.-c., Wang, S. (2023). Research on diversity and accuracy of the recommendation system based on multi-objective optimization. *Neural Computing and Applications*, 35, 5155–5163. <https://doi.org/10.1007/s00521-020-05438-w>.
- Madaan, N., Manjunatha, A., Nambiar, H., Goel, A., Kumar, H., Saha, D., Bedathur, S. (2023). DetAIL: a tool to automatically detect and analyze drift in language. In: *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 37. Association for the Advancement of Artificial Intelligence, pp. 15767–15773. <https://doi.org/10.1609/aaai.v37i13.26872>.
- Miller, Z., Dickinson, B., Deitrick, W., Hu, W., Wang, A.H. (2014). Twitter spammer detection using data stream clustering. *Information Sciences*, 260, 64–73. <https://doi.org/10.1016/j.ins.2013.11.016>.
- Mohawesh, R., Tran, S., Ollington, R., Xu, S. (2021). Analysis of concept drift in fake reviews detection. *Expert Systems with Applications*, 169, 114318. <https://doi.org/10.1016/j.eswa.2020.114318>.
- Pham, X.C., Dang, M.T., Dinh, S.V., Hoang, S., Nguyen, T.T., Liew, A.W.-C. (2017). Learning from data stream based on random projection and hoeffding tree classifier. In: *Proceedings of the International Conference on Digital Image Computing: Techniques and Applications*. IEEE, pp. 1–8. 978-1-5386-2839-3. <https://doi.org/10.1109/DICTA.2017.8227456>.
- Rao, S., Verma, A.K., Bhatia, T. (2021). A review on social spam detection: challenges, open issues, and future directions. *Expert Systems with Applications*, 186, 115742. <https://doi.org/10.1016/j.eswa.2021.115742>.
- Rathore, P., Soni, J., Prabakar, N., Palaniswami, M., Santi, P. (2021). Identifying groups of fake reviewers using a semisupervised approach. *IEEE Transactions on Computational Social Systems*, 8(6), 1369–1378. <https://doi.org/10.1109/TCSS.2021.3085406>.
- Reis, J.C.S., Correia, A., Murai, F., Veloso, A., Benevenuto, F. (2019). Explainable machine learning for fake news detection. In: *Proceedings of the ACM Conference on Web Science*. Association for Computational Linguistics, pp. 17–26. 9781450362023. <https://doi.org/10.1145/3292522.3326027>.
- Reyes-Menendez, A., Saura, J.R., Filipe, F. (2019). The importance of behavioral data to identify online fake reviews for tourism businesses: a systematic review. *PeerJ Computer Science*, 5, 1–21. <https://doi.org/10.7717/peerj-cs.219>.
- Ribeiro, M.T., Singh, S., Guestrin, C. (2016). “Why Should I Trust You?”: explaining the predictions of any classifier. In: *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. Association for Computing Machinery, pp. 1135–1144. 9781450342322. <https://doi.org/10.1145/2939672.2939778>.
- Ritu Aggrawal, S.P. (2021). Elimination and backward selection of features (P-value technique) in prediction of heart disease by using machine learning algorithms. *Turkish Journal of Computer and Mathematics Education*, 12(6), 2650–2665. <https://doi.org/10.17762/turcomat.v12i6.5765>.

- Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence*, 1, 206–215. <https://doi.org/10.1038/s42256-019-0048-x>.
- Rustam, F., Khalid, M., Aslam, W., Rupapara, V., Mehmood, A., Choi, G.S. (2021). A performance comparison of supervised machine learning models for Covid-19 tweets sentiment analysis. *PLoS One*, 16(2), 1–23. <https://doi.org/10.1371/journal.pone.0245909>.
- Škrlić, B., Martinc, M., Lavrač, N., Pollak, S. (2021). autoBOT: evolving neuro-symbolic representations for explainable low resource text classification. *Machine Learning*, 110(5), 989–1028. <https://doi.org/10.1007/s10994-021-05968-x>.
- Solari, S., Egüen, M., Polo, M.J., Losada, M.A. (2017). Peaks Over Threshold (POT): a methodology for automatic threshold estimation using goodness of fit p-value. *Water Resources Research*, 53(4), 2833–2849. <https://doi.org/10.1002/2016WR019426>.
- Song, G., Ye, Y., Zhang, H., Xu, X., Lau, R.Y.K., Liu, F. (2016). Dynamic clustering forest: an ensemble framework to efficiently classify textual data stream with concept drift. *Information Sciences*, 357, 125–143. <https://doi.org/10.1016/j.ins.2016.03.043>.
- Stirling, M., Koh, Y.S., Fournier-Viger, P., Ravana, S.D. (2018). Concept drift detector selection for hooeffding adaptive trees. In: *Proceedings of the Australasian Joint Conference on Artificial Intelligence*, Vol. 11320. Springer, pp. 730–736. https://doi.org/10.1007/978-3-030-03991-2_65.
- Stites, M.C., Nyre-Yu, M., Moss, B., Smutz, C., Smith, M.R. (2021). Sage advice? The impacts of explanations for machine learning models on human decision-making in spam detection. In: *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, Vol. 12797 LNAI. Springer, pp. 269–284. https://doi.org/10.1007/978-3-030-77772-2_18.
- Sun, N., Lin, G., Qiu, J., Rimba, P. (2022). Near real-time twitter spam detection with machine learning techniques. *International Journal of Computers and Applications*, 44(4), 338–348. <https://doi.org/10.1080/1206212X.2020.1751387>.
- Treisman, A., Mughaz, D., Stulman, A., Dvir, A. (2022). Word embedding dimensionality reduction using dynamic variance thresholding (DyVaT). *Expert Systems with Applications*, 208, 118157–118170. <https://doi.org/10.1016/j.eswa.2022.118157>.
- Upadhyay, C., Abu-Rasheed, H., Weber, C., Fathi, M. (2021). Explainable job-posting recommendations using knowledge graphs and named entity recognition. In: *Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics*. IEEE, pp. 3291–3296. 978-1-6654-4207-7. <https://doi.org/10.1109/SMC52423.2021.9658757>.
- Vaitkevicius, P., Marcinkevicius, V. (2020). Comparison of classification algorithms for detection of phishing websites. *Informatica*, 31(1), 143–160. <https://doi.org/10.15388/20-INFO404>.
- Veloso, B.M., Leal, F., Malheiro, B., Burguillo, J.C. (2019). On-line guest profiling and hotel recommendation. *Electronic Commerce Research*, 34, 100832–100841. <https://doi.org/10.1016/j.elerap.2019.100832>.
- Veloso, B.M., Leal, F., Malheiro, B., Burguillo, J.C. (2020). A 2020 perspective on “Online guest profiling and hotel recommendation”: reliability, scalability, traceability and transparency. *Electronic Commerce Research and Applications*, 40, 100957–100958. <https://doi.org/10.1016/j.elerap.2020.100957>.
- Wang, J., Han, L., Zhou, M., Qian, W., An, D. (2021). Adaptive evaluation model of web spam based on link relation. *Transactions on Emerging Telecommunications Technologies*, 32(5), 1–13. <https://doi.org/10.1002/ett.4047>.
- Wang, X., Kang, Q., An, J., Zhou, M. (2019). Drifted twitter spam classification using multiscale detection test on K-L divergence. *IEEE Access*, 7, 108384–108394. <https://doi.org/10.1109/ACCESS.2019.2932018>.
- Wu, T., Wen, S., Xiang, Y., Zhou, W. (2018). Twitter spam detection: survey of new approaches and comparative study. *Computers & Security*, 76, 265–284. <https://doi.org/10.1016/j.cose.2017.11.013>.
- Wu, Y., Sharma, K., Seah, C., Zhang, S. (2023). SentiStream: a co-training framework for adaptive online sentiment analysis in evolving data streams. In: *Proceedings of the Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, pp. 6198–6212. <https://doi.org/10.18653/v1/2023.emnlp-main.380>.
- Zhang, K.Z.K., Xu, H., Zhao, S., Yu, Y. (2018). Online reviews and impulse buying behavior: the role of browsing and impulsiveness. *Internet Research*, 28(3), 522–543. <https://doi.org/10.1108/IntR-12-2016-0377>.
- Zhang, Z., Damiani, E., Hamadi, H.A., Yeun, C.Y., Taher, F. (2022). Explainable artificial intelligence to detect image spam using convolutional neural network. In: *Proceedings of the International Conference on Cyber Resilience*. IEEE, pp. 1–5. 978-1-6654-6122-1. <https://doi.org/10.1109/ICCR56254.2022.9995839>.

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