Grading a News Website's Reliability in Real-Time Using Technical Characteristics

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Abstract

The internet has allowed misinformation to spread with little push-back enabling malicious actors to target subsets of people for cyber-attacks. Current defenses lack unbiased and immediate warnings to readers prior to reading and/or sharing news stories. In this report, a new solution is introduced which aims to deliver an unbiased and real-time news website reliability grade. The solution is achieved through a trained machine learning model on unbiased technical characteristics of recognized legitimate and misinformation sites with the machine learning model's prediction made available immediately to readers through a Google Chrome extension in the form of a letter grade. This report will share the solution details and demonstrate its high success rate as an unbiased real-time news website reliability grader and as a necessary defense from cyber-attacks through misinformation.

1. Introduction

This section outlines the goal of this report by stating the current problem, a proposed solution, and detailing the structure of the remaining report articulating how the solution was achieved.

1.1 Problem Statement

Misinformation and falsehoods now spread across the globe with ease thanks to the internet [1]. This reality has influenced perception and created divided echo chambers uninterested in open discussion and debate [2]. As a result, malicious actors can now click bait targeted audiences eager to follow the latest story and ultimately phish personal information and lead readers to install malware unknowingly [3]. Unfortunately today, controlling the spread of misinformation requires slow and manual due diligence. Therefore, there exists a need for a faster and more efficient solution to help keep society better informed and protected from cyber-attacks.

1.2 Solution Statement

For society to take steps back towards open communication and be shielded from cyber-attacks, an unbiased and real-time indicator of a news website's reliability is warranted. Thanks to the research done at Princeton University, technical characteristics of a website were discovered to be a strong indicator of a news website's legitimacy [4]. These technical characteristics (discussed further in section 4) are free of political and social preference, and therefore can act as unbiased indicators. Using these technical characteristics, a news website's legitimacy could be predicted in real-time through a machine learning (ML) model trained on technical characteristics of both legitimate and misinformation news websites. This prediction could then offer an unbiased and real-time warning to readers who may possibly refrain now from reading and sharing a potentially misinformed news article. By offering this indication, the potential spread of cyber-attacks or exploitation of readers could be thwarted and the public could become better informed.

1.3 Report Structure

The remaining sections of this report will review the solution. Section 2 will introduce the approach to the solution, and section 3 will assess related efforts and their shortcomings. Section 4 will offer an in depth explanation of how the solution works followed by section 5 which will evaluate the effectiveness of the solution. Section 6 will share current limitations of the solution, and finally, section

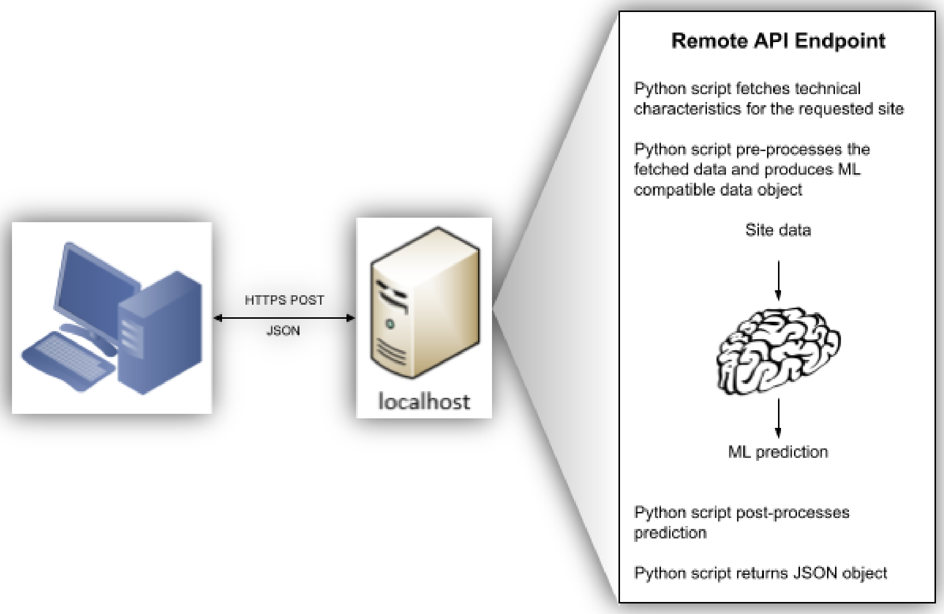

Figure 1. The request flow and logical flow the ML model remote API

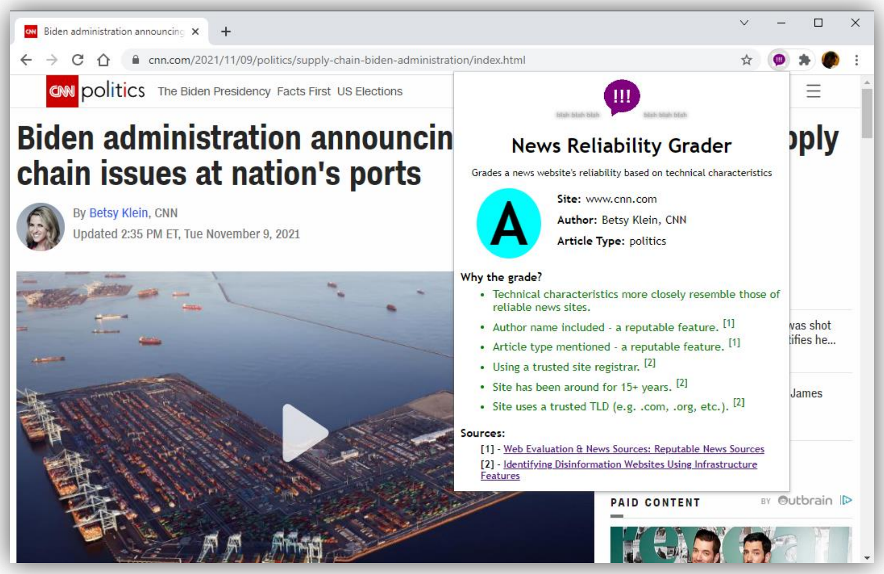

Figure 2. An example of the proposed Google Chrome extension fly-out

7 will share recommendations for future work. The report will then conclude with section 8, and share acknowledgements and references.

2. Proposal

To best protect and inform readers in real-time of misinformation, an unbiased and automatic news website grader could be an effective defense. Fortunately, extensions in Google Chrome can function automatically in the background and are integrated in the browser to evaluate any active tab. Leveraging this Google Chrome extension technology, any news website requested in a tab could have its unbiased technical characteristics automatically and immediately evaluated against a trained ML model, and have its predicted reliability reported to the reader through a fly-out from the extension's icon.

The ML model will be a classification model trained to distinguish legitimate news websites from misinformation news websites. The ML model will exist at a remote endpoint accessible through an API by which the Google Chrome extension will send prediction requests. The ML model will then respond to the Google Chrome extension with its classification prediction. Figure 1 depicts the request flow of the data and the processing logic at a high level to be performed at the remote endpoint. More details on the ML model are provided in section 4.

The Google Chrome extension will automatically issue the prediction API requests to the ML model's remote API endpoint, and upon a response, the extension will derive a familiar letter grade and display this grade along with justifications and sources to the reader in a fly-out dropped from the extension's icon in the menu bar. Figure 2 depicts an example of the fly-out. More details on the extension are included in section 4.

Through this solution, readers can quickly see the current news website's reliability grade and have either confidence in reading a highly graded news website, or hesitation in proceeding with an article on a poorly graded news website.

3. Related Works

In designing this solution, other approaches to slowing the spread of misinformation were reviewed.

Misinformation is commonly shared on social media platforms including Twitter [5]. Twitter has therefore built a crowdsourcing solution titled Birdwatch to verify and label posts as trustworthy or potentially misleading [6]. This solution is new and has performed well, however the crowdsourcing nature of Birdwatch renders its defenses slow, and possibly biased.

While reviewing published Google Chrome extensions designed to slow the spread of misinformation, several extensions stood out. These extensions are mentioned in table 1. The solutions all had reliable and accurate ratings and recommendations; however common shortcomings were a lack of a real-time answer, the requirement to subscribe to the service, and an inability to predict unfamiliar sites.

The proposed solution, however, aims to be unbiased, fast, free, and capable of evaluating entirely never before seen websites.

Technology	**PROs**	**CONs**
Twitter's Birdwatch [6]	Crowd-sourced, trustworthy	Slow
Know News [7]	Rates site on quality/credibility	Unable to rate unfamiliar sites
Newstrition [8]	Rates content/site on various metrics	
The Factual [9]	Rates based on source/journalist/language	Limited dataset, requires subscription
Thrive Verify [10]	Crowd-sourced block-chaining	Slow, requires subscription
Trusted Times [11]	ML analyzes content	

Table 1. Similar Google Chrome extensions to the proposal with listed pros and cons

4. Methodology

A solution which could best combat the problem of misinformation spreading requires both an unbiased decision indicating the reliability of the information, and making that decision available immediately. An unbiased decision is essential for bringing polarized communities back together towards trusting the same reliable sources of information. Furthermore, making the decision available immediately is also essential in preventing the acceptance and spread of misinformation.

The method by which this solution was achieved involved two primary components – a trained ML model, and a Google Chrome extension.

4.1 The Machine Learning Model

A trained ML model offers the benefits needed for the solution. They are capable of offering highly accurate predictions and are capable of issuing these predictions very quickly. The following sections share how an ML model was developed and trained to deliver these benefits.

4.1.1 Background

Researchers at Princeton University discovered disinformation websites could be identified using the infrastructure features of a website [4]. The researchers gathered 33 infrastructure features including domain, certificate, and hosting features, and trained an ML model with these features from legitimate, disinformation, and non-news websites. The ML model was then capable of classifying a website as legitimate, disinformation, or non-news with an accuracy of 98%, 95%, and 98% respectively.

Given these findings, the goal of indicating a news website's reliability in an unbiased and fast fashion became a viable possibility. These infrastructure features are free of political and social preference and in no way on their own favor one perspective over another. Furthermore, a trained ML model is capable of producing a prediction very quickly – especially compared to manual due diligence by an individual.

Therefore, the Princeton University research project and its findings offer a foundation to achieving an optimal solution to the stated problem.

4.1.2 Building the ML Training Dataset

To develop an ML model capable of distinguishing a legitimate news website from a misinformation news website, the ML model must be trained. To train the ML model, technical characteristics from a sample of both legitimate and misinformation news websites must be digested by the ML model.

4.1.2.1 Acquiring Sample Websites

Enough sample websites were needed to produce a reliable prediction in real-time. In the end, 429 commonly recognized as reputable news websites were recorded from trusted sources [12-16]. Additionally, 477 news websites which were repeatedly reviewed and flagged as misinformation news websites by more reputable sources were recorded [17-20]. Together, these 906 websites had their technical characteristics collected which made up the training dataset.

4.1.2.2 The Technical Characteristics

The technical characteristics which helped drive an unbiased classification of a news website exist across several categories. The technical characteristics used in the solution exist in table 2.

4.1.2.2.1 Domain Characteristics

A website's domain carries with it many characteristics. Domain names must be registered and some registrars are more reputable than others [4]. These registrars may be operated in various countries, can offer privacy options, and be either cheap or expensive [21]. Legitimate news websites observably favor more reputable registrars which carry with it a higher price tag.

Additionally, domain names are registered for a length of time. The longer a registration is held for, the more expensive the registration costs. Legitimate news websites honor these regular payments and have more than likely existed online for a significant length of time. Furthermore, a public reputation of reliability also takes time to materialize further indicating older news domain names mostly belong to legitimate news websites.

Moreover, certain characters contained within the domain name itself can be suspicious such as numbers and special characters. Most legitimate news websites observably do not include special characters.

Characteristic	Data Type	Category	Source
News Keyword(s) in Domain	Binary	Domain	Python script method
Domain Name Length	Numeric	Domain	Python script method
"News" in Domain	Binary	Domain	Python script method
WHOIS Privacy	Binary	Domain	WHOIS API
Registrar Name	Text	Domain	WHOIS API
Nameserver SLD	Text	Domain	WHOIS API
Registrant Name	Text	Domain	WHOIS API
Registrant Organization	Text	Domain	WHOIS API
Registrant Country	Text	Domain	WHOIS API
Time Since Domain Registration	Numeric	Domain	WHOIS API
Domain Lifespan	Numeric	Domain	WHOIS API
Time to Domain Expiration	Numeric	Domain	WHOIS API
Time Since Domain Update	Numeric	Domain	WHOIS API
Novelty TLD	Binary	Domain	Python script method
Digit in Domain	Binary	Domain	Python script method
Hyphen in Domain	Binary	Domain	Python script method
Domain Resolves	Binary	Domain	SSL API
SAN Count	Numeric	Certificate	SSL API
SAN Contains Wildcard	Binary	Certificate	SSL API
Expired Certificate	Binary	Certificate	SSL API
Certificate Available	Binary	Certificate	SSL API
Self-Signed Certificate	Binary	Certificate	SSL API
Certificate Issuer Name	Text	Certificate	SSL API
Certificate Issuer Country	Text	Certificate	SSL API
Certificate Lifetime	Numeric	Certificate	SSL API
Website AS	Text	Hosting	IP Info API
Website Country	Text	Hosting	IP Info API
CDN Provider	Text	Infrastructure	IP Info API

Table 2. The technical characteristics used in the ML training dataset

4.1.2.2.2 SSL Certificate Characteristics

SSL certificates offer secure communications between the reader's device and the rest of the internet. A website protected by an SSL certificate indicates the website cares about the safety of their readers in the cyber world.

SSL certificates must be purchased from Certificate Authorities (CA) and paid for based on a specified validity period. Some CAs, however, may offer fast and cheap certificates. Legitimate news websites tend to use highly trusted CAs, and validity periods which stretch longer periods of time.

4.1.2.2.3 Other Characteristics

Websites also require hosting. Web hosting is another paid for service which can, again, either be cheap or expensive. Hosting is available across the globe, but most legitimate news websites noticeably host their website within the same geographical region the content of the website relates to.

Additionally, a content delivery network (CDN) helps improve a website's accessibility. Integrating and paying for this service is another indicator of a news website's legitimacy.

4.1.2.3 Acquiring the Technical Characteristics

The technical characteristics listed in table 2 were collected for the 906 recorded websites. In order to achieve this, several available API libraries in Python were leveraged.

The WHOIS API performs the ICANN domain registration lookup [22]. This API supplied most of the domain-related technical characteristics. The IPInfo API helped supply useful hosting technical characteristics [23], and the request/socket APIs helped acquire SSL certificate technical characteristics. Finally, basic string analysis helped identify certain traits about the characters contained within the domain name itself.

4.1.3 Building and Training the ML Model

To construct the ML model, the deep learning libraries of Keras and TensorFlow were chosen as they are open-source libraries supported for Python [24]. The ML model was designed to be a binary classification model given that its goal was to predict a news website as legitimate or not. The training dataset was ingested as either continuous (for numerical and binary data elements) or categorical (for textual data elements) and fed into a Sequential model with three layers. Additionally, the "ReLU" activation algorithm [25] and the "HeNormal" weight initialization algorithm [26] were used. Finally, the ML model was compiled for optimization with the "Adam" algorithm [27] and minimized loss with the "Binary Cross-Entropy" algorithm [28]. Each of these algorithms are recommended selections for binary classification models. The model was then trained 200 times with the training dataset at which point the accuracy had reached near perfect scores. More on the ML model's accuracy is included in section 5.

4.1.4 The ML Model API

In order for the ML model to service prediction requests, an API to the ML model was built. To accomplish this, a simple PHP web application was implemented to receive HTTP POST requests. The PHP endpoint then instantiates a Python script in the cgi-bin directory of the web application forwarding to it the request payload. The Python script would then execute, and then respond back to the PHP application which would forward the result in its response payload. Figure 3 depicts the HTTP POST API along with its request and response objects labeled.

4.1.4.1 The API Request

The API endpoint expects a JSON object with a single key/value pair over HTTP POST. The expected key is "siteToAnalyze" and its value would be a website's domain name. This domain name value would then be passed along to the Python script.

4.1.4.2 The Python Script Logic

The Python script was responsible for several functions. First, the script would use the Klazify API to determine if the domain supplied belonged to a news website or not [29]. If it did not, the script would skip its remaining operations and respond with default details.

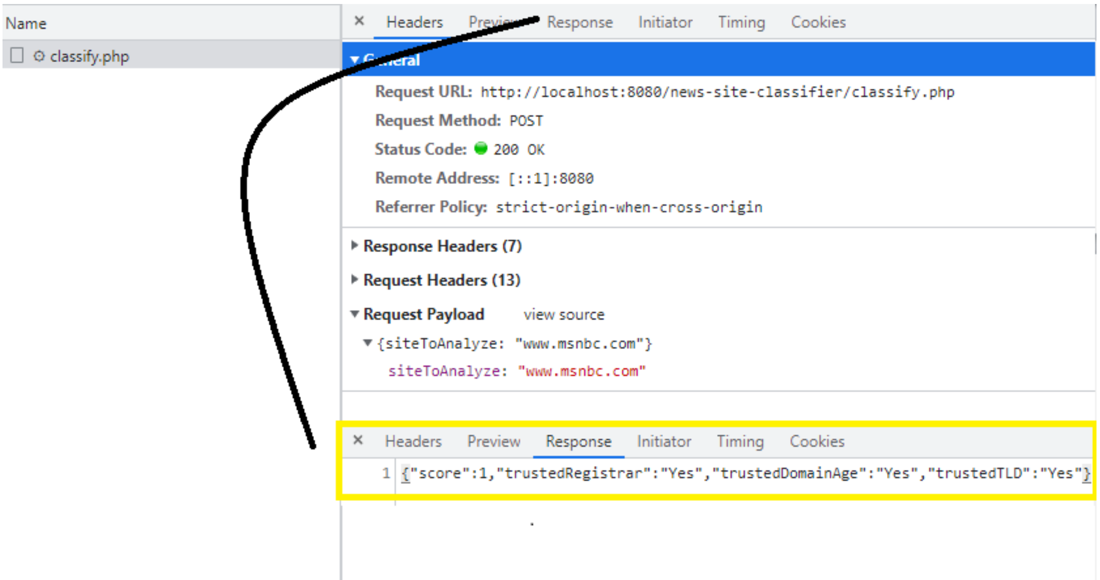

Figure 3. The HTTP POST API in action to the PHP endpoint

If the domain was determined to be a news website, the technical characteristics in table 2 were acquired for the domain using the APIs mentioned in section 4.1.2.3 to prepare a dataset compatible with the ML model. With the technical characteristics in hand for the requested domain, the details were fed into the ML model for a prediction to be made. The prediction call either returns a 1 for legitimate, or 0 for misinformation.

Because some technical characteristics were observed as strong indicators of a legitimate news website from the training dataset, these technical characteristics were included in the response. These characteristics are:

1. The domain uses a highly trusted registrar – Yes or No
    a. Through manual inspection of the training dataset, three registrars were identified as only used by legitimate news websites – Network Solutions LLC, MarkMonitor Inc., and CSC Corporate Domains Inc.
2. The domain age is at least 15 years old – Yes or No
    a. Through manual inspection of the training dataset, the vast majority of legitimate news websites were 15 years old or older.
3. Is a common top-level-domain (TLD) used – Yes or No
    a. Through manual inspection of the training dataset, all legitimate news websites used a common TLD while some misinformation websites used novelty TLDs. Common TLDs include com, org, net, int, edu, gov, mil, and arpa.

4.1.4.3 The API Response

The Python script would then respond with a JSON object containing four key/value pairs – the ML prediction along with the 3 promising technical characteristics. This JSON object would then be promoted back out as the API response of the PHP web application. If the site was not categorized as a news website, the ML prediction value was -1, and the three other key/value pairs had empty values.

4.2 The Google Chrome Extension

Presenting a news website’s predicted legitimacy to a reader almost immediately is the other half of the proposed solution. Fortunately, Google Chrome’s extension feature offers the ability to both perform background operations and display information to readers.

```html
▼<article class="pg-rail-tall pg-rail--align-right " itemscope itemtype="https://schema.org/NewsArticle"> == $0
   <meta itemprop="isPartOf" content="news">
   <meta itemprop="articleSection" content="opinions">
   <meta itemprop="dateCreated" content="2021-10-20T22:35:27Z">
   <meta itemprop="datePublished" content="2021-10-20T22:35:27Z">
   <meta itemprop="dateModified" content="2021-10-20T22:35:27Z">
   <meta itemprop="url" content="https://www.cnn.com/2021/10/20/opinions/facebook-name-change-ceo-zuckerberg-alaimo/index.html">
   <meta itemprop="author" content="Opinion by Kara Alaimo ">
   <meta itemprop="headline" content="Opinion: Facebook, don't change your name -- change your CEO - CNN">
   <meta itemprop="description" content="Facebook's reported move to change its name is a smart PR move, says Kara Alaimo, but won't get to the root
   or magically create a brand in which consumers will place blind faith. Replacing Mark Zuckerberg as CEO is a different story, she contends.">
   <meta itemprop="keywords" content="opinions, Opinion: Facebook, don't change your name -- change your CEO - CNN">
   <meta itemprop="image" content="https://cdn.cnn.com/cnnnext/dam/assets/201022112637-mark-zuckerberg-1023-file-super-tease.jpg">
   <meta itemprop="thumbnailUrl" content="https://cdn.cnn.com/cnnnext/dam/assets/201022112637-mark-zuckerberg-1023-file-super-tease.jpg">
   <meta itemprop="alternativeHeadline" content="Facebook, don't change your name -- change your CEO">
 ▼<div class="l-container">
     <h1 class="pg-headline" data-act-id="article_head_0">Facebook, don't change your name -- change your CEO</h1>
   ▶<div class="metadata ">…</div>
   ▶<div class="pg-rail-tall__wrapper">…</div>
     ::after
   </div>
   <div class="pg-below-rail"></div>
 </article>
```

Figure 4. A sample of the Schema.org "NewsArticle" content for a news article on CNN.com

4.2.1 Background Operations

The Google Chrome extension performs a sequence of steps prior to displaying results to a reader.

4.2.1.1 API Call to the ML Model

The Google Chrome extension's background logic kicks off when a change to the active tab occurs. Upon this event, the domain name is identified and added to a JSON object for delivery to the HTTP API endpoint. The API is called and upon its successful return, the response JSON object is stored into Chrome storage.

4.2.1.2 Identifying Page Level Details

Publishers at UC Merced Library documented the inclusion of author name and article type as characteristics of reputable news sources [30]. Therefore, making mention of these in the Google Chrome extension served to benefit readers as well as the trustworthiness of the extension itself.

To identify these page level details, the Schema.org "NewsArticle" HTML template was leveraged [31]. This template included meta details about the page and the article. Included in the meta details were "author" and "articleSection" (articleSection being synonymous with article type). Both these page level details were fetched and also stored into Chrome storage. Figure 4 depicts an example of the Schema.org "NewsArticle" details for an article on CNN.com.

4.2.2 Producing the Fly-Out Display

With the site data now available in Chrome storage, the Google Chrome extension could now produce the fly-out display for a reader to see the results. These results included several components:

1. A familiar letter grade scoring the article's reliability
2. The site name
3. The author's name
4. The article type
5. Justifications for the grade
6. Sources to back the justifications

4.2.2.1 The Letter Grade Algorithm

To produce a reliable and acceptable letter grade for a news article, three factors were considered. They were:

1. The ML model's prediction where 1 was legitimate, and 0 was misinformation
2. The inclusion of the author name or the inclusion of the article type.
3. Whether the article type was an opinion piece or not

These factors were chosen because the ML model's prediction is the main driving force behind this solution's evaluation of unbiased criteria. Furthermore, the inclusion of author or article type are considered reputable features. And finally, opinion pieces are inherently biased and therefore must be read carefully. As a result, the grading algorithm flows as such:

1. Each site begins with the letter grade of a C.
2. If the ML model's prediction is that the site is legitimate, the grade will shift upward to a B. Else, the grade shifts downward to an E.
3. If the author name and/or article type are mentioned, the current letter grade shifts upward. Else, the letter grade remains the same.
4. If the article type is an opinion piece, the current letter grade shifts downward. Else the letter grade remains the same.

A visual representation of this algorithm is shown in figure 5.

4.2.2.2 Justifications and Sources

To help deliver more faith in the results to readers, several justifications for the grade are mentioned. These justifications speak to the findings on the article and website and are color-coded to indicate a positive trait (green), a warning (orange), or concern (red). These justifications include:

1. A statement saying the technical characteristics more closely resemble legitimate or misinformation news sites.
2. If the author and/or article type were included, confidence in this reputable feature is shared. But if they were not included, concern that they were missing is shared.
3. If the article type was an opinion piece, a warning message is shared.
4. If any of the three encouraging technical characteristics returned in the API were true, they were shared.

To support the justifications, sources were also included. To support the claims regarding author and article type, UC Merced Library's documented source was included. To support the claims regarding technical characteristics, the research study performed by Princeton University was included. Figure 2, 6-1, and 6-2 demonstrate the extension's resulting fly-out for three news website examples.

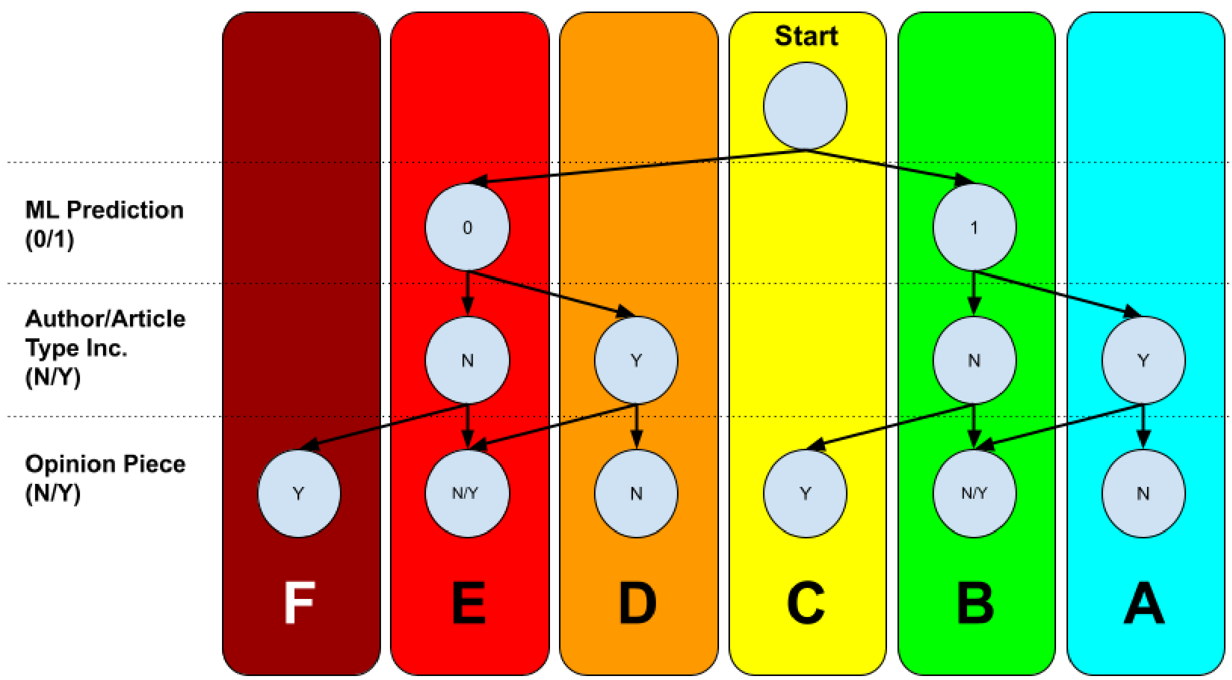

Figure 5. The grading algorithm depicting all potential paths to each letter grade

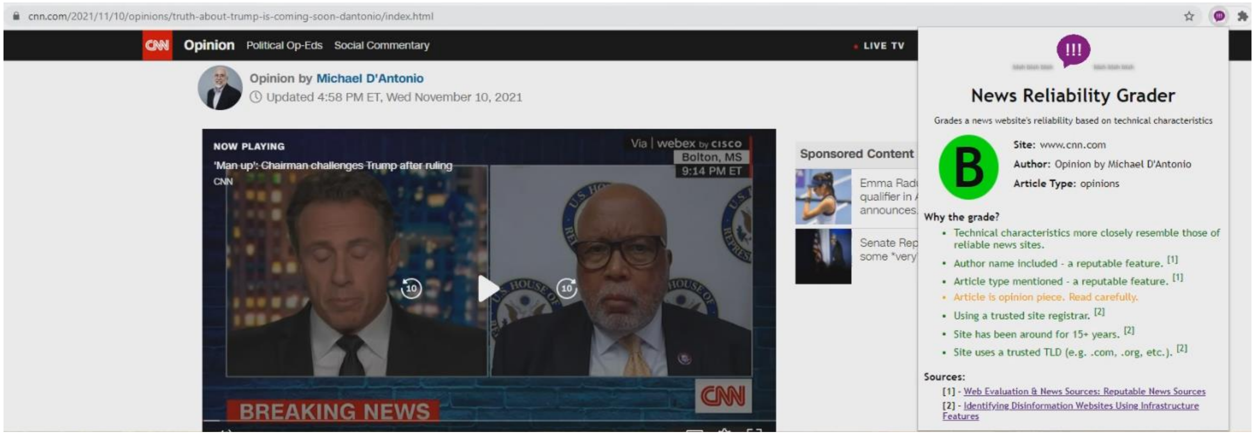

Figure 6-1. The fly-out of the Google Chrome extension for an opinion piece article on a legitimate news website

Figure 6-2. The fly-out of the Google Chrome extension for a misinformation news website

5. Evaluation

Two evaluation methods were performed to determine the efficacy of the proposed solution.

5.1 ML Model Accuracy

The ML model was evaluated by performing 200 iterations over two random subsets of the training dataset. The first random subset included 50% of the training dataset, and the second random subset included 75% of the training dataset.

Both tests demonstrated a quick jump to >90% accuracy in the early iterations while maintaining the high level accuracy for the remaining iterations. The test performed on 75% of the training dataset did ultimately reach perfect accuracy while the other test only reached 99%. Figure 7-1 and 7-2 demonstrate these results in a graph.

Therefore, the conclusion which could be drawn from these results is enough training data was collected to reach a highly accurate ML model, and training the ML model with the entire dataset can offer a highly accurate prediction for a news website's legitimacy.

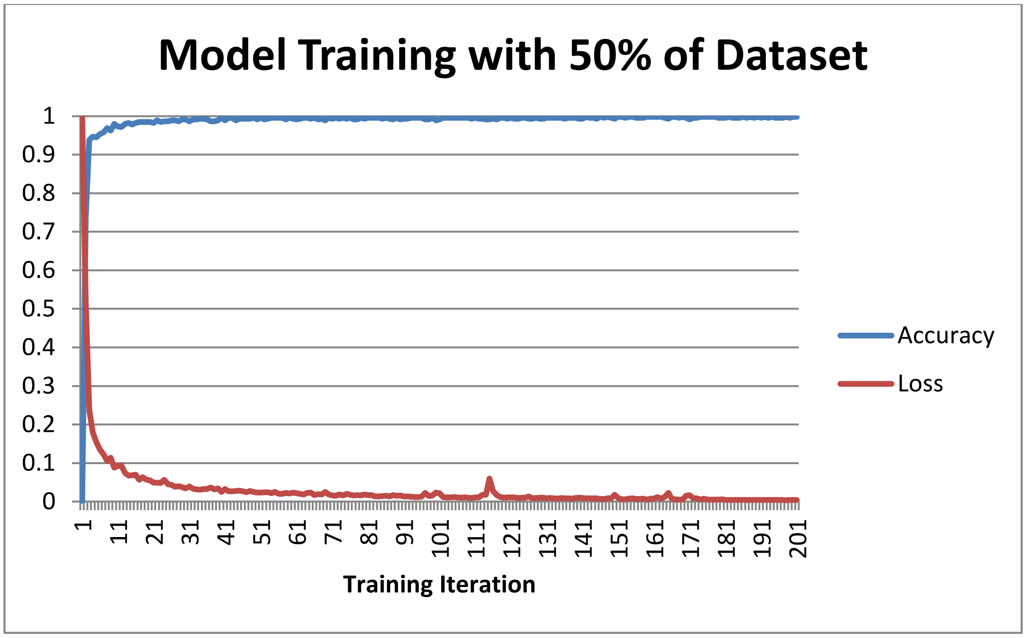

Figure 7-1. Training accuracy and loss while training with 50% of the dataset

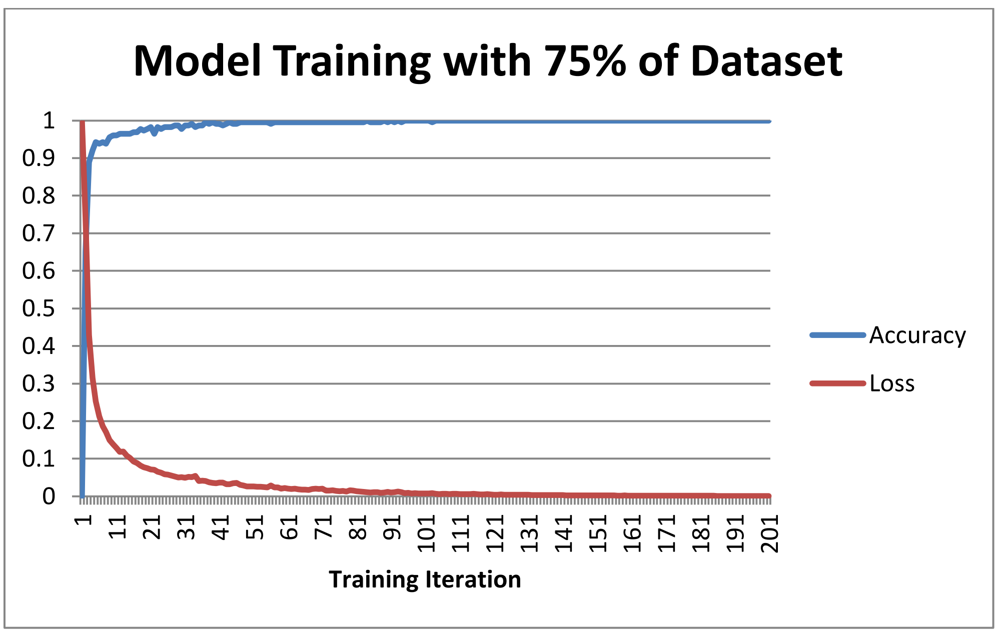

Figure 7-2. Training accuracy and loss while training with 75% of the dataset

5.2 Google Chrome Extension Accuracy

To evaluate the real-time accuracy of the complete solution, The Google Chrome extension's results were analyzed by manually visiting 50 legitimate news websites and 50 misinformation news websites and recording the extension's resulting grade. These websites and their results are shared in figure 8-1 and 8-2.

After visiting the 100 sites, 47 of the 50 legitimate news websites were correctly graded, and 49 of the 50 misinformation news websites were correctly graded. The resulting accuracy of the real-time evaluation was therefore 96%.

Legitimate Site	Grade	ML Score	Author Identified	Article Type Identified	Opinion Piece	Trusted Registrar	Trusted Domain Age	Trusted TLD	Grade Appropriate?
dailybruin.com	B	1	No	No	No	No	Yes	Yes	Yes
illinoistimes.com	B	1	No	No	No	Yes	Yes	Yes	Yes
inlander.com	B	1	No	No	No	Yes	Yes	Yes	Yes
kctv.com	B	1	No	No	No	Yes	Yes	Yes	Yes
leoweekly.com	B	1	No	No	No	No	Yes	Yes	Yes
suntimes.com	B	1	No	No	No	Yes	Yes	Yes	Yes
theadvocate.com	B	1	No	No	No	Yes	Yes	Yes	Yes
villagevoice.com	B	1	No	No	No	No	Yes	Yes	Yes
wyomingnews.com	B	1	No	No	No	No	Yes	Yes	Yes
yumasun.com	B	1	No	No	No	No	Yes	Yes	Yes
dailyherald.com	B	1	No	No	No	Yes	Yes	Yes	Yes
dmcityview.com	B	1	No	No	No	No	Yes	Yes	Yes
journalstar.com	B	1	No	No	No	No	Yes	Yes	Yes
laraza.com	B	1	No	No	No	No	Yes	Yes	Yes
njherald.com	B	1	No	No	No	Yes	Yes	Yes	Yes
theday.com	B	1	No	No	No	No	Yes	Yes	Yes
yahoo.com	B	1	No	No	No	Yes	Yes	Yes	Yes
yellowstone.net	B	1	No	No	No	Yes	Yes	Yes	Yes
cbs4boston.com	B	1	No	No	No	Yes	Yes	Yes	Yes
clarionledger.com	B	1	No	No	No	Yes	Yes	Yes	Yes
fredericksburg.com	B	1	No	No	No	No	Yes	Yes	Yes
nypress.com	B	1	No	No	No	Yes	Yes	Yes	Yes
signonsandiego.com	B	1	No	No	No	Yes	Yes	Yes	Yes
westword.com	B	1	No	No	No	No	Yes	Yes	Yes
abqjournal.com	B	1	No	No	No	Yes	Yes	Yes	Yes
bozemandailychronicle.com	B	1	No	No	No	No	Yes	Yes	Yes
cnn.com	A	1	Yes	Yes	Yes	Yes	Yes	Yes	Yes
foreignaffairs.com	B	1	No	No	No	Yes	Yes	Yes	Yes
newsminer.com	B	1	No	No	No	Yes	Yes	Yes	Yes
politico.com	B	1	No	No	No	No	Yes	Yes	Yes
presstelegram.com	B	1	No	No	No	Yes	Yes	Yes	Yes
riverfronttimes.com	B	1	No	No	No	No	Yes	Yes	Yes
spectrumlocalnews.com	E	0	No	No	No	Yes	No	Yes	No
stargazettenews.com	B	1	No	No	No	Yes	Yes	Yes	Yes
theunionleader.com	B	1	No	No	No	Yes	Yes	Yes	Yes
adn.com	B	1	No	No	No	No	Yes	Yes	Yes
autonews.com	B	1	No	No	No	No	Yes	Yes	Yes
bloomberg.com	B	1	No	No	No	Yes	Yes	Yes	Yes
buffalo.com	B	1	No	No	No	No	Yes	Yes	Yes
buzzfeed.com	B	1	No	No	No	Yes	No	Yes	Yes
dailyregister.com	B	1	No	No	No	Yes	Yes	Yes	Yes
theintercept.com	E	0	No	No	No	No	No	Yes	No
weeklystandard.com	E	0	No	No	No	No	Yes	Yes	No
abcnews.go.com	B	1	No	No	No	Yes	Yes	Yes	Yes
artvoice.com	B	1	No	No	No	No	Yes	Yes	Yes
columbusalive.com	B	1	No	No	No	Yes	Yes	Yes	Yes
okgazette.com	B	1	No	No	No	Yes	Yes	Yes	Yes
qctimes.com	B	1	No	No	No	No	Yes	Yes	Yes
engadget.com	B	1	No	No	No	Yes	Yes	Yes	Yes
nationalreview.com	B	1	No	No	No	Yes	Yes	Yes	Yes

Figure 8. The Google Chrome extension results for legitimate news websites

Misinformation Site	Grade	ML Score	Author Identified	Article Type Identified	Opinion Piece	Trusted Registrar	Trusted Domain Age	Trusted TLD	Grade Appropriate?
callthecops.net	E	0	No	No	No	No	No	Yes	Yes
theonion.com	E	0	No	No	No	Yes	Yes	Yes	Yes
gellerreport.com	E	0	No	No	No	No	No	Yes	Yes
whydontyoutrythis.com	E	0	No	No	No	No	No	Yes	Yes
higherperspectives.com	E	0	No	No	No	No	Yes	Yes	Yes
worldtruth.tv	E	0	No	No	No	No	No	Yes	Yes
gulagbound.com	E	0	No	No	No	No	No	Yes	Yes
rogue-nation3.com	E	0	No	No	No	No	No	Yes	Yes
teddystick.com	E	0	No	No	No	No	No	Yes	Yes
infowars.com	E	0	No	No	No	No	Yes	Yes	Yes
occupydemocrats.com	E	0	No	No	No	No	No	Yes	Yes
thelapine.ca	E	0	No	No	No	No	No	Yes	Yes
thelastlineofdefense.org	E	0	No	No	No	No	No	Yes	Yes
therundownlive.com	E	0	No	No	No	No	No	Yes	Yes
americasfreedomfighters.com	E	0	No	No	No	No	No	Yes	Yes
newzmagazine.com	E	0	No	No	No	No	No	Yes	Yes
zerohedge.com	E	0	No	No	No	No	No	Yes	Yes
usanewshome.com	E	0	No	No	No	No	No	Yes	Yes
freewoodpost.com	E	0	No	No	No	No	No	Yes	Yes
dailystormer.su	E	0	No	No	No	No	No	Yes	Yes
stuppid.com	E	0	No	No	No	No	No	Yes	Yes
coasttocoastam.com	E	0	No	No	No	Yes	Yes	Yes	Yes
associatedmediacoverage.com	E	0	No	No	No	No	No	Yes	Yes
en-volve.com	E	0	No	No	No	No	No	Yes	Yes
a-news24.com	E	0	No	No	No	No	No	Yes	Yes
smag31.com	E	0	No	No	No	No	No	Yes	Yes
theblaze.com	E	0	No	No	No	No	Yes	Yes	Yes
newspunch.com	B	1	No	No	No	No	Yes	Yes	No
fprnradio.com	E	0	No	No	No	No	No	Yes	Yes
stillnessinthestorm.com	E	0	No	No	No	No	No	Yes	Yes
thenet24h.com	E	0	No	No	No	No	No	Yes	Yes
breitbart.com	E	0	No	No	No	No	Yes	Yes	Yes
viralcocaine.com	E	0	No	No	No	No	No	Yes	Yes
prntly.com	E	0	No	No	No	No	No	Yes	Yes
nationalreport.net	E	0	No	No	No	No	No	Yes	Yes
americanjournalreview.com	E	0	No	No	No	No	No	Yes	Yes
democraticunderground.com	E	0	No	No	No	No	No	Yes	Yes
therightists.com	E	0	No	No	No	No	No	Yes	Yes
thepoliticalinsider.com	E	0	No	No	No	No	Yes	Yes	Yes
thirdestatenewsgroup.com	E	0	No	No	No	No	No	Yes	Yes
thedcgazette.com	E	0	No	No	No	No	No	Yes	Yes
globalresearch.ca	E	0	No	No	No	No	Yes	Yes	Yes
bigamericannews.com	E	0	No	No	No	No	No	Yes	Yes
beforeitsnews.com	E	0	No	No	No	No	No	Yes	Yes
newsmutiny.com	E	0	No	No	No	No	Yes	Yes	Yes
realfarmacy.com	E	0	No	No	No	No	No	Yes	Yes
huzlers.com	E	0	No	No	No	No	No	Yes	Yes
darkoutpost.com	E	0	No	No	No	No	No	Yes	Yes
thespoof.com	D	0	No	Yes	No	No	Yes	Yes	Yes
counterpsyops.com	E	0	No	No	No	No	No	Yes	Yes

Figure 9. The Google Chrome extension results for misinformation news websites

6. Limitations

While the solution was evaluated to be quite accurate, several limitations do exist.

The training dataset for the ML model heavily favored domain traits. While these traits did prove to be valuable, including more hosting details and details of the technology stack could further help the accuracy of the prediction.

Furthermore, the method by which the author and article type are identified proved to be unreliable. Unfortunately, the Schema.org "NewsArticle" template is not widely used, and therefore isn't a reliable method for identifying the author's name or article type.

Finally, the solution is currently only supported on the desktop version of the Google Chrome browser.

7. Future Work

The following recommendations are made for evolving the solution in the future to best protect and keep readers informed.

Most misinformation is spread over social media platforms through Facebook shares and Twitter posts [5]. Therefore, expanding the solution to crawling embedded links on webpages and labeling these embedded links with grades could help prevent readers from clicking misinformation sources and also resharing the post. Furthermore, to address the supported platform limitation, expanding support to additional desktop browsers as well as mobile browsers would help a greater number of readers.

Combining this solution with additional due diligence efforts such as author reputation lookup, validation of listed sources, and natural language processing (NLP) of the text to detect tone and intention could deliver the best defense to readers from malicious misinformation websites.

To address the challenge of identifying the author and article type, using a separate trained ML model on news article HTML code seems to be a leading solution for identifying these attributes [32-34]. Incorporating this technology into the solution can help deliver more confidence in the grading solution.

Additionally, offering verified and trusted alternative websites or articles related to the topic currently being read could help steer readers away from misinformation sources and back to safety with reliable sources.

And finally, no solution is best without offering an opportunity to readers to supply feedback on their experience, or refute a given grade for a news website. Reader input can be vital in constructing a reliable solution, and collecting this feedback could help the solution reach a more optimal state.

8. Conclusion

The spread of misinformation has been leading the public towards information bubbles and cyber-attacks. A new solution which is unbiased and immediate is necessary to curb the spread of misinformation and keep readers safe from cyber-attacks. It has been shown in this report that using unbiased technical characteristics to train an ML model to predict a news website's reliability and making that prediction available immediately to readers through a Google Chrome extension could help in slowing the spread of misinformation, and bring readers back together on common ground and protected from cyber-attacks. The solution outlined in this report achieved a near perfect prediction rate through theoretical evaluation, and 96% accuracy through practical evaluation. Much is still necessary to do to end the spread of misinformation, but with the solution and results outlined in this report serving as a foundation; a viable means for truly ending the spread of misinformation and cyber-attacks may be in reach.

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Appendix A

To access the software for this solution, please follow this link: https://github.com/georgebasil/CS-6727-News-Reliability-Grader