CrediBench: Building Web-Scale Network Datasets for Information Integrity

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Abstract

Online misinformation poses an escalating threat, amplified by the Internet's open nature and increasingly capable LLMs that generate persuasive yet deceptive content. Existing misinformation detection methods typically focus on either textual content or network structure in isolation, failing to leverage the rich, dynamic interplay between website content and hyperlink relationships that characterizes real-world misinformation ecosystems. We introduce CrediBench: a large-scale data processing pipeline for constructing temporal web graphs that jointly model textual content and hyperlink structure for misinformation detection. Unlike prior work, our approach captures the dynamic evolution of general misinformation domains, including changes in both content and inter-site references over time. Our processed one-month snapshot extracted from the Common Crawl archive in December 2024 contains 45 million nodes and 1 billion edges, representing the largest web graph dataset made publicly available for misinformation research to date. From our experiments on this graph snapshot, we demonstrate the strength of both structural and webpage content signals for learning credibility scores, which measure source reliability. The pipeline and experimentation code are all available here, and the dataset is made publicly available on huggingface.

1 Introduction

The digital information landscape is evolving at an unprecedented pace. While the open nature of the Internet has democratized access to information, it has also amplified the scale, speed and reach of misinformation propagation. This phenomenon not only distorts public discourse but can also undermine democratic processes, public health, and social cohesion [22, 32, 38]. In fact, experts rated misinformation and disinformation as the number one imminent risk the world faces in 2024-25 [19]—urgently calling for the development of systems to ensure information veracity. The rise of generative AI further compounds this challenge: Large Language Models (LLMs) can now produce text that is increasingly indistinguishable from human-generated content [13], making misinformation more persuasive and far harder to detect at the user level.

Fortunately, AI also stands as a key path to a solution, making large-scale, advanced automated assessments possible. However, existing approaches fail to preserve all aspects of web data that factor into misinformation detection—the textual content of websites, their diverse nature and relations, and their temporal and structural relations—especially at scale. Relatedly, proposed solutions have been recognized to lack robust generalizability (to out-of-distribution data, but also to new topics and emerging information generation techniques) [26, 47]. These methods are often catered to the

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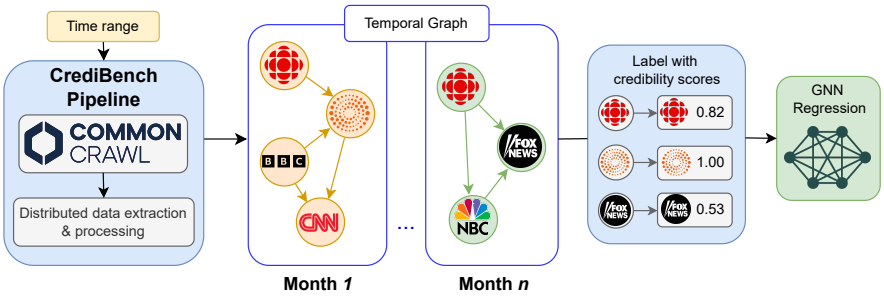


Figure 1: Overview of the CrediBench pipeline. Common Crawl data is extracted and processed to produce temporal web graphs, where nodes are web domains and edges hyperlinks. These temporal graphs, annotated with human-evaluated credibility scores, are passed to Graph Neural Networks (GNNs) for them to learn the regression task of assigning credibility scores.

small scale of existing datasets, which usually span over a limited time window or a single platform [41, 43, 34, 25, 51, 36]. These datasets fail to recognize the comprehensive, general-scoped and open nature of the Internet and how it affects information propagation. Thus, the weight of this issue on the real world calls for urgent principled systems to automate credibility assessments online at scale, which would significantly enhance the capacity to detect misinformation.

In this work, we introduce the CrediBench framework which enables an automated pipeline for assigning credibility scores to web domains, quantifying their degree of misinformation, by providing large-scale temporal text-attributed graphs that preserve both the structural and content-rich characteristics of online information sources. The temporal graph curated by CrediBench is large-scale, evolving and contains text content for its nodes, thus providing ample opportunities to apply both natural language processing techniques as well as graph ML methods for credibility score assignment to measure source reliability. Our main contributions are as follows:

- **Graph construction pipeline.** We introduce a pipeline to retrieve, decompress and construct large-scale web graphs, as illustrated in Figure 1. The pipeline builds data from Common Crawl [17], a data provider that has been crawling and making available large-scale web data on a monthly basis. Our pipeline holistically preserves the structural, temporal, and semantic facets of web data, by constructing rich temporal graphs—up to 150 million nodes and more than a billion edges per snapshot—while extracting domain-level textual and structural signals. The textual content can be embedded as node features, enabling principled graph-based learning for web domain credibility assessment.
- **Large-scale, general-scoped web graph.** We present a one-month snapshot obtained through our pipeline, specifically from December 2024. This graph has upwards of a billion edges and is annotated with human-generated credibility labels. This is one of the largest graph datasets available to date, making it an ideal foundation for future research on the credibility of web domains. Given this dataset's rich attributes and reflective real-world nature, we hope this addresses the lack of benchmark datasets in real-world applications [6].
- **Structure and text are strong signals for learning credibility.** Through experiments with both GNNs and embedded text domain content, we show that both relational and text context of the web domains provide strong signals for assigning their credibility score. This demonstrates the importance of our proposed CrediBench and the need to model both structural and textual features of web domains for credibility assignment.

Reproducibility: The code for the pipeline and experiments is made available at `https://github.com/ekmpa/CrediGraph`. The dataset is made publicly available at `https://huggingface.co/datasets/ekmpa/CrediBench`.

2 Related work

Traditional Misinformation Detection Efforts to assess the credibility of online information sources have ranged from manual, expert-driven evaluations to computational methods. Manual approaches

include user-focused frameworks such as the CRAAP test [7] or the SIFT framework [12]. Expert knowledge is also often leveraged, and most datasets for credibility on the web rely on such human annotation [37]. However, such manual methods are inherently unable to scale to modern information flows. To address this, machine and deep learning methods quickly emerged as a strong solution. These efforts have largely focused on credibility assessments at the claim level, using endogenous signals from the text, such as linguistic and stylistic features, semantic content, and multimodal cues [54, 15, 30, 46, 34]. These text features have been roughly categorized into *stylistic* features, *complexity* features and *psychological* features, all tied to disinformation detection [13]. However, these signals fail to model the complex web structure of misinformation websites and information propagation. As such, exogenous signals, such as social endorsement cues, have also been integrated in some of these works [11, 25, 43, 52, 41], but to a much lesser extent. Moreover, such works focusing on the claim-level inherently ignore the more general nature of the issue: misinformation spreads across sources and platforms, and detecting whether a certain piece of text contains misinformation largely benefits from assessing its source and other online entities' interactions with it.

LLM Based Misinformation Detection Approaches to credibility assessments online are increasingly exploring the role of LLMs for misinformation detection [14, 44, 29]. Particularly, Retrieval-Augmented Generation (RAG) has shown promise for this, as introduced in [49] which uses RAG agents for evidence-based misinformation detection. RAG indeed renders LLMs more factual and up-to-date, both crucial for detecting misinformation [49, 8, 40]. However, existing works fail to preserve all aspects of web data that factor into information veracity; namely content, structural and temporal patterns. Many are based on content, often at the claim level again, extracting features from the text. Some include social context, which can be divided into social engagement and social networks [13]; but these are weaker in the relational information they contain than entire, large-scale text-attributed web graphs.

Graph Based Methods Considering the importance of content, structural and temporal patterns, finding a principled method to incorporate all three is very compelling. Using graphs enables the modelling of complex relations between information sources and the propagation of credibility [39], as information online does not exist in isolation. For example, these approaches often leverage graph-structured data, sometimes building on link analysis algorithms [9] and using them as features to learn from [42, 42], or using graph knowledge bases [28]. Most use modern GNNs to capture propagation patterns of credibility signals through message passing [48, 55, 36]. For instance, [55] propose a dual-channel graph attention mechanism that jointly captures link structure and propagation dynamics, and [45] integrates heterogeneous graph data and adversarial active learning to better handle the diversity and noise present in online information ecosystems. While temporal graphs are particularly compelling considering they can model the dynamic nature of information propagation, their use for this task remains largely unexplored.

3 Preliminaries

We first introduce the graph notations for the temporal text-attributed graph constructed from the CrediBench pipeline. As the Common Crawl data is released monthly, we represent the graph as a sequence of graph snapshots, similar to the Discrete-time Dynamic Graph setup defined in [31]. The data formulation is as follows:

Definition 1 (Temporal text-Attributed Graphs) *A Temporal text-Attributed Graph (TAG)* $\mathbf{G}$ *is a sequence of graph snapshots sampled at regularly-spaced time intervals and nodes have evolving text content at each snapshot:*

$$\mathbf{G} = \{\mathbf{G}_0, \mathbf{G}_1, \ldots, \mathbf{G}_T\}$$

$\mathbf{G}_t = \{\mathbf{V}_t, \mathbf{E}_t\, \mathbf{X}_t\ \}$ *is the graph at timestamp* $t \in [0, T]$*, where* $\mathbf{V}_t \in \mathbb{R}^{|\mathbf{V}_t|}$*,* $\mathbf{E}_t \in \mathbb{R}^{|\mathbf{V}_t| \times |\mathbf{V}_t|}$ *are the set of nodes and edges in* $\mathbf{G}_t$ *and* $\mathbf{X}_t \in \mathbb{R}^{|\mathbf{V}_t| \times L}$ *is the text feature of nodes in* $\mathbf{G}_t$ *where* L *is the maximum text length. Note that* $\mathbf{X}_t$ *stores the raw text content from each web domain and can be then processed into text embedding vectors for models to use.*

Definition 2 (Temporal Node Regression Task) *Let* $\mathbf{G}_t \in \mathbf{G}$ *be snapshot* t *of TAG* $\mathbf{G}$ *and* $\mathbf{V}_t$ *is the set of vertices in* $\mathbf{G}_t$*. Let* y *be the true labeling function over nodes in* $\mathbf{V}_t$*, where* $y : \mathbf{V}_t \to [0, 1]$*. The goal of the temporal node regression task is to learn a function* $f : \mathbf{V}_t \to [0, 1]$ *that approximates* y*:*

$$f(v) = y(v); \forall v \in \mathbf{V}_t$$

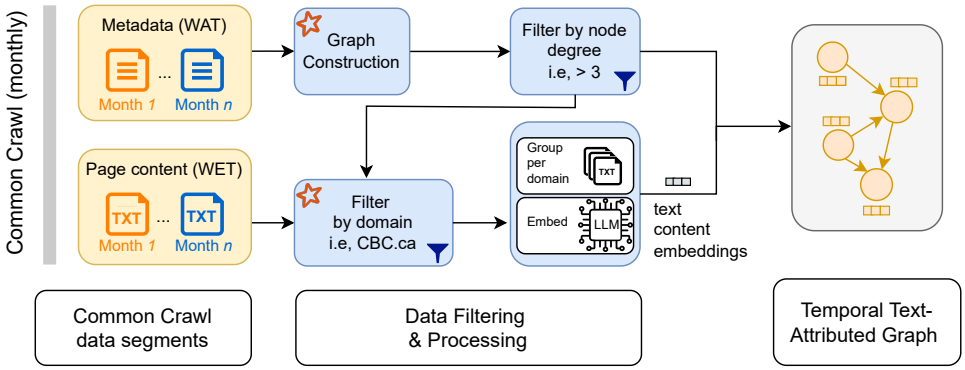


Figure 2: The temporal graph construction pipeline is implemented on a PySpark cluster to process Common Crawl domains collected across multiple months. WAT file segments are used to construct the domain-level web graph, with nodes of degree ≤ 3 excluded. Domain-level textual content is extracted from WET files, aggregated, and embedded with an off-the-shelf large language model to initialize node features. Edge timestamps are assigned based on the first day of the week of the crawl (usually, the first week of the month).

Note that across multiple timestamps, the label of a node might evolve as well.

Domain credibility assignment task. The domain credibility assignment task is the main temporal node regression task we support on CrediBench. The Credibility scores are assigned to the graph by matching domain names between the graph nodes and the entities of the Domain Quality Ratings (DQR) dataset [37]. The DQR dataset comprises approximately 11.5K web domains annotated with credibility scores collected from six different expert sources, including media organizations and independent professional fact-checkers. These sources apply different scoring schemes and evaluate domains across multiple dimensions (e.g., trust, reliability, bias, and transparency). Among these scores, we use the Media Bias/Fact Check (MBFC) score [2], which relies on human fact-checkers from the International Fact-Checking Network to assess media outlets on criteria such as factual accuracy and bias. In addition, we employ the first principal component (PC1), introduced by the DQR and derived from a principal component analysis (PCA) of the six scoring sources. The PC1 serves as an aggregate credibility measure that captures the common signal across the diverse sources, thereby mitigating variations between them. Both of these measures are in the range of $[0, 1]$ where a higher score indicates better credibility and less misinformation.

4 CrediBench

Figure 2 shows the detailed CrediBench pipeline for constructing our temporal text-attributed web graphs, where a one-month snapshot may contain upwards of a billion edges. The data provided by Common Crawl is in Web ARChive (WARC) files [1], the industry standard for web archiving. Metadata used to build the graph is found in Web ARChive Timestamp (WAT) files, containing HTTP response headers, links extracted from HTML pages and other metadata. Additionally, WARC Encapsulated Text (WET) files contain extracted plain text from web content.

Graph construction. The first step in graph construction is to download and decompress the raw data based on Common Crawl's decompression pipeline [16]. The downloaded files contains about 90,000 instances for one month, which are iteratively processed in batches of 300. After decompressing the files, the metadata and domain hyperlinks are extracted, resulting in a web graph where each node is a web domain, and each edge a hyperlink from one web domain's page to another. When aggregating over batches, deduplication is performed on the list of domains while subdomains and their parent domain are counted as separate nodes, i.e., `domain.com` and `domain.com.news`.

Domain filtering. Following the entire graph's decompression and construction, we attach credibility scores when available from [37], as well as timestamps at a monthly granularity (as provided in Common Crawl web graphs). We then filter domains in the graph to discard nodes with degree below a threshold which we set to 3. This processing step is motivated by the fact that lower-degree (especially isolated) nodes are less likely to be relevant during retrieval queries or generally in

information searches, and removing them lightens the computational load of handling the graph. A threshold 0 effectively means eliminating all isolated nodes, that of 1 eliminates also leaves, and so on. A threshold of 3, as we set it here, seeks a balance between this and the information loss it entails.

Text content extraction. Given the list of domains present in the graph, we extract text content for the web domains by loading their scraped content provided by Common Crawl WET file format, which stores the extracted plain body text of pages from the original HTML. A distributed Spark cluster is employed to process approximately 7.3 TB of WET files [18] in batches adjustable to the available compute resources. Each job extracts the text content, scraping timestamp, content languages, and corresponding webpage URL for the subsequent text classification task. The number of textual documents associated with each domain varies according to its update frequency; for instance, in the December 2024 snapshot, `github.com` contains approximately 20,000 documents, whereas other domains may contain only a single document. In the document grouping step, all documents belonging to a given domain alongside their timestamps are appended into a single document to facilitate subsequent embedding generation. To construct representative samples, we retain the three longest and three shortest documents per domain and merge them for embedding. For domains lacking textual content, we employ a multi-threaded online scraping pipeline in batches to extract text directly from the domain's home page.

Example December 2024 Snapshot. To explore the structural characteristics of credible websites, we utilize the CrediBench loading pipeline to yield a one-month snapshot from December 2024 [2]. Table 1 details the structure of the December 2024 raw and processed web graphs constructed through the CrediBench pipeline; where the processed one has only nodes with degree strictly higher than 3. We use the latter for experiments in this paper. Processing the graph as such keeps 90.21% of edges and 33.98% of nodes, thus slightly increasing the graph's density. The final processed file size of edges is 8.78 GB.

Table 1: Features of the December 2024 web graph.

Feature	Raw	Processed
$\|V\|$	132,547,562	45,041,648
$\|E\|$	1,124,576,420	1,014,523,552
Isolated nodes (deg = 0)	1,404,051	11,395
Leaves (deg = 1)	67,946,252	28,857
Edge density	1.28e-07	1.00e-06
Min. degree	0	0
Max. degree	14,900,588	14,719,077
Mean degree	16.97	45.05

In this paper, our analysis centers on a one-month snapshot, and these initial results already highlight the strength of such patterns in signaling credibility. Nevertheless, we anticipate that temporal dynamics will exert an equally significant influence, given the inherently evolving nature of web domains and online information propagation. Preliminary analyses of subgraphs from October and November 2024 further underscore this expectation, revealing clear signs of structural evolution. For instance, up to 40% of overlapping nodes experience an increase in out-degree from one month to the next. These observations motivate future research aimed at systematically examining the role of dynamic patterns in shaping credibility signals.

5 Experiments

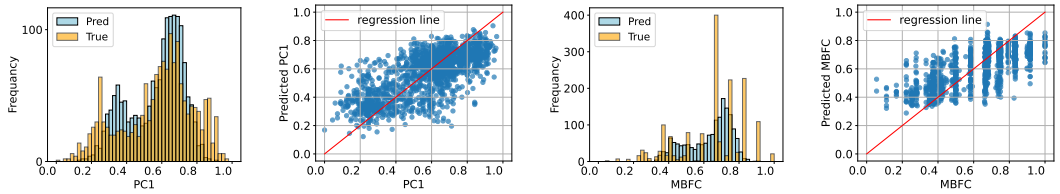
We experimented on the December 2024 snapshot to gain insights on signals that can infer the credibility of a domain. We aim to answer the following three research questions in our experiments:

- **RQ1:** *to what extent does the text content of a domain indicates its credibility score?*
- **RQ2:** *to what extent does the hyperlink structure of a web domain inform its credibility score?*
- **RQ3:** *to what extent can we benefit from combining the graph structure with the text content?*

Dataset: We use the domain quality rating dataset DQR [37] and its extracted textual content to train and test all models. We split the dataset into 60%, 20%, and 20% for train, validation, and test set splits. The regression targets on the DQR datasets are the PC1 and MBFC scores.

Compared Methods. To empirically examine all three research questions, we include a range of models to learn the text and graph modalities in our dataset, including the following:

[2]With Crawl ID `CC-MAIN-2024-51`.



(a) PC1 Score Distribution.

(b) PC1 regression scatter plot.

(c) MBFC Score Distribution.

(d) MBFC regression scatter plot.

Figure 3: Domain text provides the MLP with a clear signal for predicting the PC1 and MBFC scores.

- **Text-Based Models:** We employ the classic **TF-IDF** representation to embed each domain's textual content. The resulting embeddings are used as input to Multi-Layer Perceptron (MLP) decoder to predict the score.
- **LLM-based Models:** We also use various LLM models of different sizes to embed the text content into a latent vector, including: *EmbeddingGemma-300M* [21], *Qwen3 (0.6B and 8B)* embedding models [53], and *OpenAI Text Embedding 3 Large (OpenAI-TE3L)* [3]. Then, the text embeddings are fed to the MLP regressor for score prediction.
- **Graph-Based Models:** We utilize several Graph Neural Network (GNN) models: GCN[33], GraphSAGE[27], GAT[50], and GATv2 [10], to learn the hyperlink structure among domains and predict credibility scores.
- **Graph + Text Model:** We combine graph embeddings(from GAT) and text embeddings (from OpenAI-TE3L) to form joint feature representations. These combined embeddings are fed into an MLP regressor for credibility prediction. In the paper, refer to the *GAT+OpenAI-TE3L+MLP* model as the *graph+text* model.

We report regression results for the PC1 and MBFC scores in Table 2. We also include the simple mean baseline for comparison, which always predicts the mean score of all domains. To better understand models' performance, we report both the Mean Absolute Error (MAE) as well as the Maximum Absolute Error (Max AE) in both tables. The MAE reflects overall performance across many domains, while the Max AE reflects the worst possible deviation from the ground-truth score.

RQ1: Regression with text content. Here, we aim to answer if the extracted web text content contains beneficial signals for predicting domain credibility scores. This question is reflected by the performance of *text-based* models and *LLM-based* models as shown in Table 2. All models using learned text features outperform the mean baseline for both scores. This shows that the text content in CrediBench provides significant signals for credibility prediction when embedded via various methods (LLM or TF-IDF). Across both PC1 and MBFC scores, we observe that the LLM with the most parameters, i.e. OpenAI-TE3L, is the best performer in the text-only category. In addition, within the same Qwen3 family, more parameters also enables significantly better performance. We observe up to 0.014 MAE improvement from Qwen3-0.6B to Qwen3-8b on the PC1 score and up to 0.008 MAE improvement on the MBFC score. Figure 3 highlights a noticeable signal between the textual content of web domains and their assigned credibility scores. The Mean Absolute Error (MAE) for the test set PC1 and MBFC are 0.119 and 0.105, compared to 0.167 and 0.153 with the mean predictor. Therefore, incorporating the temporal evolution of domain content into CrediBench appears to be a promising direction. Figures 3a and 3c illustrate how the textual content facilitated the model in learning the distribution of credibility scores. Additionally, Figures 3b and 3d depict the deviations of predicted scores from the true scores, reflecting the achieved MAE performance.

RQ2: Regression with graph structure. To understand the impact of graph structure in modeling credibility scores, we train Graph Neural Networks (GNNs) on the node regression task on the December 2024 snapshot. For all GNN models, we use the Random Node Initialization [4] (RNI) as the node feature, normally distributed in $\mathcal{N}(0, 1)$. Our experiments include four common GNN architectures: two classical GNNs, GCN [33] and GraphSAGE (SAGE) [27], and two attention-based GNNs, Graph Attention Network (GAT) [50] and GATv2 [10]. In table 2, we report the average of 3 random seeds. We observe that with RNI initialization, GNNs consistently outperform the mean baseline. In particular, we see that the GAT model provides the lowest MAE in both the PC1 score as well as the MBFC score under graph based models. This indicates that the hyperlink graph structure provides useful signal for credibility prediction. Additionally, we also experimented with using

Table 2: Performance comparison (MAE; lower is better) of graph, text and LLM based models. Best **first** and second results are highlighted in bold.

	Score Type	PC1		MBFC	
	Metric	**MAE**	**Max(AE)**	**MAE**	**Max(AE)**
	Mean	0.167	0.546	0.153	0.561
Text-only	Text TF-IDF	0.130$\pm$0.001	**0.484**	0.117$\pm$0.001	**0.414**
	Gemma-300M + MLP	0.142$\pm$0.001	0.557	0.119$\pm$0.001	0.536
	Qwen3-0.6B + MLP	0.137$\pm$0.001	0.602	0.122$\pm$0.001	0.536
	Qwen3-8B + MLP	0.135$\pm$0.001	0.516	0.116$\pm$0.001	0.454
	OpenAI-TE3L + MLP	0.119$\pm$0.001	0.514	0.105$\pm$0.001	0.770
Graph-only	GCN	0.130$\pm$0.001	0.837	0.118$\pm$0.001	0.766
	GraphSAGE	0.152$\pm$0.002	0.852	0.135$\pm$0.004	0.892
	GAT	0.128$\pm$0.002	0.806	0.115$\pm$0.020	0.765
	GATv2	0.130$\pm$0.001	0.793	0.117$\pm$0.001	0.830
	graph + text	**0.117**$\pm$0.0001	0.523	**0.101**$\pm$0.0001	0.471

zero initialization instead of RNI as initial node features for GNNs, we observe a sharp decline of performance, we believe that in this snapshot, the increased expressiveness from RNI is beneficial for GNNs in learning the task, detailed results are reported in Appendix F. For further ablations, we report the effect of varying the number of neighbours and the number of hops in sampling Appendix G, we find that using more hops with 10-50 neighbours sampled achieves better performance. While maintaining one-hop, but with an overall equal number of neighbours produces worse performance.

RQ3: Combining graph and text. Since the dataset provides rich graph and text features, combining both may achieve the best performance. By concatenating the graph embeddings from GAT and text embeddings from OpenAI-TE3L LLM to form an input representation to a task MLP, the resulting graph+text model is trained to combine both modalities. Table 2 shows that the graph+text model achieves the best MAE. The graph+text MLP learns to extract complementary yet strong signals from both modalities. This is a promising first look into how to leverage the unique and novel features in CrediBench datasets and future work can further extend on this idea.

6 Conclusion

In this work, we introduced CrediBench, a large-scale web graph construction pipeline accompanied by a 1-month snapshot obtained through it, on which we explore the strength of different signals, including structural and text content, in learning credibility scores. Indeed, our empirical findings show that it is important to model both the text and graph structures of web domains in order to achieve better credibility score assignment. Our results strongly motivate further work to incorporate these signals, which in turn motivates the exploration of temporal aspects in dynamic evolution as greater leverage for predicting credibility scoring of web domains. In turn, such scores should facilitate the tracking and detection of misinformation at scale. By providing this pipeline and the resulting dataset, we aim to advance the field of misinformation detection, which is crucial in today's digital age where LLM-generated content is increasingly permeating digital ecosystems.

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A Limitations

Relying on Common Crawl web graphs as its data source, the CrediBench pipeline may inherit some of its features, which we cannot verify. Coverage may be biased, for example, capturing domains unequally, or noisy text content, all of which may affect the quality of our data and limit the strength of insights drawn from it. Similarly, with our small labelled set relative to all the domains, we are limited in the credibility we can effectively infer. Moreover, we recognize that, despite our best efforts, considering the large scale of the data, running the CrediBench can be expensive in its computational requirements. With this consideration, we will release our curated December 2024 snapshot after the review period for ease of access. Finally, our current experiments are based on the December 2024 snapshot only, which already contains billions of edges. We are actively running CrediBench to extract additional snapshots and will share publicly for research purposes once they are available.

B Broader Impact

Positive impact in graph learning. Misinformation is becoming more and more prevalent online. Therefore, it is important to design ML methods to detect misinformation domains. To this end, CrediBench constructs a dataset which benefits the community by introducing better baseline datasets for misinformation detection. Additionally, this dataset provides a large-scale real-world dataset for graph ML, which is beneficial as a benchmark for the field.

Negative societal impact. The nature of credibility score assignment can bring potential negative impact, especially if a learned model incorrectly assigned low or high credibility score. In addition,

credibility and misinformation can be subjective depending on the individual; thus it is important to be aware of such impact when deploying a ML system for misinformation detection. Lastly, due to the nature of our labels on the web domains, they are biased towards news websites, thus focusing more on a certain type of domains.

C Compute

For the data downloading, decompressing and graph construction, constructing one monthly snapshot takes around 600 hours for all batches on a single NVIDIA RTX8000 with 265GB of RAM and 4 CPU cores. Downstream degree-based filtering and target label generation for supervised learning consume an additional 7 hours per monthly snapshot of upwards of a billion edges, with the same computational setup. To enable this, this step offloads sorting and joins to disk-backed external processed and temporary files to avoid costly in-python accumulators. We also use memory-mapped degree vectors to avoid loading large structures into RAM, and performing streaming, sequential passes that minimize in-memory state. The result pipeline processes massive graphs efficiently while remaining resource-bounded and reproducible.

Extracting a monthly snapshot of textual content requires approximately 100 hours on a single high-performance virtual machine equipped with 256 GB of RAM and 64 vCPU cores. The content embeddings for the DQR dataset domains were generated separately on a V100D-16C vGPU with 16 GB of VRAM, requiring about 2 hours. To facilitate GNN on our large-scale graph, we use a neighbour loader sampler (sampling multi-hop neighbours) to sample adequate training batches of size 50 at 3-hops ($[50, 50, 50]$). The experiments were run using a 80GB memory NVIDIA A100 Tensor Core GPU.

D Text content

Text embedding generation. The content of each domain is transformed into an embedding using the Qwen3-0.6B multilingual embedding model [53], which produces 1024-dimensional representations per domain that could be downsized into smaller dimensions (i.e., 128) as it supports Matryoshka Representation Learning (MRL) [35]. Notably, Qwen3-0.6B ranks fourth on the MTEB leaderboard while being the smallest model among the top-performing models [20]. Figure 4 shows the relative sizes of the Common Crawl December-2024 webgraph that consists of 132.5M nodes, and the processed subgraph that contains 45M nodes, while the DQR labeled dataset contains only 11.5K nodes.

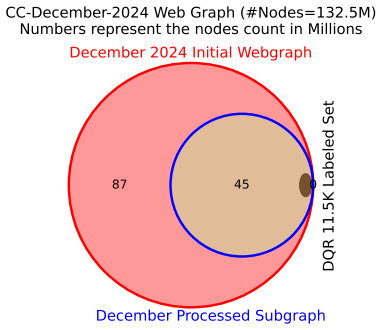

Figure 4: The relative sizes of CC-December 2024 webgraph, the processed subgraph, and the DQR.

Domain content examples with their PC1 and MBFC scores. The following examples present text content extracted from CC-WET files for various DQR domains, along with their corresponding credibility scores. The higher the score, the more credible the domain.

Domain Name: ncdc.noaa.gov	**PC1 Score: 0.90**	**MBFC Score: 0.84**

News | National Centers for Environmental Information (NCEI)
Skip to main content
An official website of the United States government
Here's how you know
Federal government websites often end in .gov or .mil. Before sharing sensitive information, make sure you're on a federal government site.
There's a lot going on at NCEI. Discover more about us and Earth's climate, oceans, coasts, and geophysics in these featured news stories.
October 4, 2024
Helene Devastates Southeast, Impacts NOAA NCEI Headquarters
NCEI headquarters in Asheville, NC, has been severely impacted by Hurricane Helene. All of our employees and staff have been accounted for with all data holdings–including paper and film records–safe.
Read More ....

Domain Name: ctvnews.ca	**PC1 Score: 0.92**	**MBFC Score: 0.91**

How many people in Canada have died from COVID? | CTV News
FOLLOW ON CORONAVIRUS UPDATES Complete coverage at CTVNews.ca/Coronavirus
COVID-19 NEWSLETTER
Text:
July 19, 2022 update: This tracker is no longer being maintained but it will continue to be available as an archive. As the collection and dissemination of provincial COVID-19 data has evolved over time, we've made available a new version of the tracker here.
Jan. 14, 2022 update: The CTV News coronavirus tracker is now highlighting hospitalizations and ICU admissions across Canada, with an interactive map that includes provincial breakdowns. Our original tracker which has been keeping count of cases since March 2020 hasn't gone anywhere, it's right below the hospitalizations.
Numbers on map reflect total hospitalizations including ICU admissions. Line graph below breaks down hospitalization and ICU admissions for each province and territory
Across Canada-Cases-Total
...

Domain Name: nbcsports.com **PC1 Score: 0.76** **MBFC Score: 0.79**

Login | NBC Sports - NBC Sports
Skip navigation
Search Query Submit Search
MLB NFL NBA NHL NASCAR
....
Top News
NASCAR Cup starting lineup at Talladega: Michael McDowell wins pole
Dustin Long,
Tyrrell Hatton ties Old Course record to lead; Nicolas Colsaerts one back after albatross
Associated Press,
WATCH: Dog steals Gareth Bale's ball on green at Dunhill Links
Golf Channel Staff,
Top Clips
Neville: 'The pressure is enormous' on ten Hag
Extended HLs: Everton v. Newcastle Matchweek 7
Talladega brings size, speed, tradition to Alabama
...

Domain Name: foxnews.com **PC1 Score: 0.53** **MBFC Score: 0.58**

Tego Calderón Rocks Washington Heights | Fox News
Go Back Fox News Move Back ADVERTISEMENT Skip
Published December 9, 2016 - 6 Images
Tego Calderón Rocks Washington Heights
Tego Calderón took the stage in New York City's Highbridge Park and gave a free concert for the Washington Heights community.
Start Slideshow
read more Facebook Twitter Email Link

Domain Name: climate.news **PC1 Score: 0.07** **MBFC Score: 0.11**

Climate News | Climate News & Climate Studies
sustainable living
01/08/2018 / By Zoey Sky
A new kind of magic mushroom: New sustainable material made of mushrooms can provide housing, food security, water filtration
While some people are worried that we might one day run out of building materials, a group of experts has revealed that they have successfully created wood-like blocks out of mushrooms. Architect Chris Maurer and his collaborators at Redhouse Architecture in Cleveland, Ohio, aim for the creation of whole communities using mushroom "wood" and its [. . .]
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All trademarks, registered trademarks and servicemarks mentioned on this site are the property of their respective owners.

Table 3: Performance comparison (MAE) of different graph neural network architectures (zero initializations) and MLP on **pc1-score** and **MBFC-score**. Qwen3-0.6B[53] text embeddings are used as MLP input features. Best results are highlighted in bold.

Method	PC1 (MAE)	MBFC (MAE)
Mean	0.167	0.153
Text only (MLP + Qwen3)	**0.137** ± **0.001**	**0.122** ± **0.001**
GCN (zero)	0.186 ± 0.030	0.254 ± 0.004
GraphSAGE (zero)	0.189 ± 0.028	0.252 ± 0.031
GAT (zero)	0.296 ± 0.051	0.153 ± 0.001
GATv2 (zero)	0.321 ± 0.040	0.302 ± 0.020

Domain Name: naturalnews.com **PC1 Score: 0** **MBFC Score: 0.11**

Preventing liver damage with the henna plant – NaturalNews.com
Home Brighteon Prep with Mike Interviews Audio Books
Download Our App About Us FAQs Search
Sections-Follow Us-Podcast-Store Subscribe-Home Politics Culture Health - Medicine Finance - Economy Prepping - Survival Science Technology-Popular Articles-Today Week
See More Popular Articles
Health Ranger Report
2:42:03 Brighteon Broadcast News, Oct 9, 2024 Hurricanes, fires and floods all designed to DESTROY cities, then REBUILD as open-air PRISON CAMPS
18:14 Unconfirmed reports: Israel preparing for pre-emptive NUCLEAR strike on Iran
26:26 FEMA setting a TRAP for Floridians to try to provoke a REVOLT
....

E Experimental Setup

The DQR dataset splitting. The DQR domains are stratified according to the target scores (i.e., PC1 and MBFC) and partitioned into training, validation, and test sets comprising 60%, 20%, and 20% of the data, respectively

MLP Experiment. A scikit-learn MLP regressor with two hidden layers (the first of dimension 128, the second 64) with a ReLU activation function, an Adam optimizer, and a learning rate of 0.001 is applied. The models were trained for 15 epochs with a maximum number of iterations set to 200.

GNN Experiment. We used different GNN architectures, such as residual connections, which performed well in node-regression tasks [5]. Each GNN has 3 layers, a dropout of 0.1, and a learning rate of 0.001 on the Adam optimizer. Due to the scale of our dataset, we employed the use of PyG's NeighborLoader [23, 24], a neighbor sampling method introduced in [27] to mini-batch our data. Each GNN runs for 100 epochs over 3 trials.

F Comparing RNI initialization with zero-vector embeddings

In Table 3, we report the performance of GNNs with zero initialization. As it highlights, this set-up does not outperform the mean baseline, as opposed to using RNI initializations. We also note that with this set-up, the standard deviation is generally increased.

G Ablation Studies on GNN experiments

In this section, we study the effect of the number of neighbors on the performance of GNNs for the PC1 score prediction. We report Out of Memory as OOM. The first observation is that generally as more number of neighbors are sampled, the GNN MAE performance on the PC1 score has improved. Similarly, in most cases, increasing the number of hops also improves the MAE score especially in

Table 4: Ablation study of GAT for PC1 score regression with varying numbers of neighbours sampled and hops. Large-scale one-hop settings are shown separately. Error is recorded in MAE.

Num Neighbors	**PC1 (MAE)**		
	1-hop	**2-hop**	**3-hop**
10,000	0.144 ± 0.001	N/A	N/A
125,000	0.145 ± 0.001	N/A	N/A
5	0.147 ± 0.001	0.148 ± 0.001	0.150 ± 0.002
10	0.141 ± 0.004	0.143 ± 0.003	0.138 ± 0.002
30	0.138 ± 0.003	0.137 ± 0.001	**0.129 ± 0.002**
50	0.142 ± 0.002	0.135 ± 0.001	OOM

the case of sampling 30 neighbors for each of three hops. This shows that multi-hop information and neighborhood information in the hyperlink graph helps with PC1 score prediction. We also conducted an experiment where a large number of 1 hop neighbors are sampled. In this case, we see that even with over 125k 1 hop neighbors, 3 hop information remains the best performer.

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