Spatial Layouts in News Homepages Capture Human Preferences

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Abstract

Information prioritization plays an important role in the way humans perceive and understand the world. Homepage layouts serve as a tangible proxy for this prioritization. In this work, we present NewsHomepages, a large dataset of over 3,000 new website homepages (including local, national, and topic-specific outlets) captured twice daily over a three-year period. We develop models to perform pairwise comparisons between news items to infer the human preferences expressed in homepage layouts, showing over 0.8 F1 score across the majority of tested cases. We apply our models to rank-order a collection of local city council policies passed over a ten-year period in San Francisco, assessing their "newsworthiness". Our findings lay the groundwork for leveraging implicit organizational cues to deepen our understanding of information prioritization.

1 Introduction

The way humans spatially organize information reflects a key signal of preference (Miller, 1956). The homepages of news organizations are one such artifact where spatial organization can be studied at scale: meticulously crafted by professional human editors, their layouts reflect the informational preferences of newspapers (Boukes et al., 2022) and shape public perception.

We draw on the growing field of weak supervision (Ratner et al., 2017; Zang et al., 2021) to extract signals of editorial preference from homepage layouts. In much the same way that preference models for reinforcement learning from human feedback (RLHF) leverage community interactions like Reddit upvotes (Ouyang et al., 2022; Bai et al., 2022), we use spatial features as implicit labels for article importance. While these cues are not explicit judgments from editors, they are consistent and structured enough to support robust modeling. To this end, we introduce *NewsHomepages*, the first large-scale dataset of homepage layouts, consisting

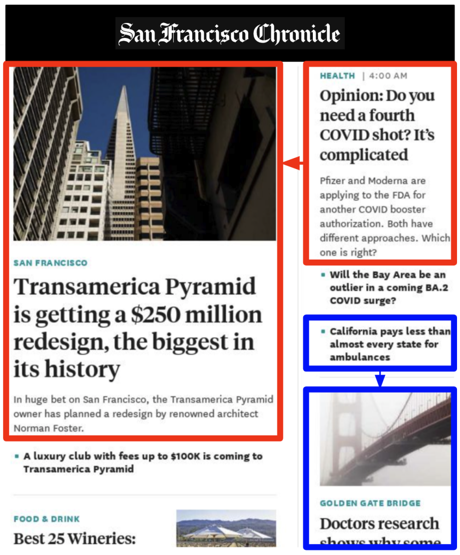


Figure 1: Two "newsworthiness" signals that editors make to guide reader attention are shown above. (1) **Position** (i.e. articles that are placed above, ↑, and left, ← relative to other articles are more important Hays (2018)). (2) **Size** (i.e. articles that are larger than other articles are more important) (3) **Graphics and Font** (i.e. articles with graphics and images are more important). We release *NewsHomepages*, a large dataset of over 3,000 homepages, collected twice-daily over three years, study information prioritization in this setting. We show can model these decisions at scale and demonstrate the usefulness of these models on two downstream tasks.

of 363k snapshots from over 3,000 news outlets spanning local, national, and topic-specific publishers, collected by consortium of over 30 computer scientists, journalists and activists. We then ask two primary research questions:

- *How well can spatial layout signals be used to model editorial preferences?*
- *Do these editorial preferences generalize across news outlets and non-news corpora?*

To answer these questions, we train preference models that that <u>*take as input pairs of texts and predict which is preferred*</u>, as a binary judgment, based on weak signals from *spatial* positioning (described further in Section 5). In addition, to learn better spatial layouts, we develop a novel bootstrapping approach to robustly parse homepage screen snapshots and determine precise spatial positions of news articles on homepages. *By interpreting positional cues as indicators of preference, our preference models infer the relative importance of information and achieve over 0.8 F1 score in many of the scenarios we tested.*

Next we demonstrate the utilize of such preference models on two downstream experiments; in each, we applied our models to rank-order a list of text. In the first experiment, we use preferences models trained on one homepage to sort the news articles of another. We find surprising nuances: for instance, despite *Breitbart* (a right-leaning outlet) being topically dissimilar to *Mother Jones* (a left-leaning outlet), their newsworthy preferences are among the most correlated of outlets we studied. In the second analysis, we used each preference models from multiple outlets to rank-order local city council policies passed in San Francisco (Spangher et al., 2023). By assessing these policies' "newsworthiness" through the lens of preference models, we highlight how implicit cues in information structure can transfer between domains and serve as useful tools (in this case, to help human journalists find relevant story-topics). Our contributions are as follows:

- We introduce NewsHomepages, large-scale dataset of hompage layouts from over 3,000 local, national and topic-specific news organizations, and develop bootstrapped parsing models to accurately parse articles on these homepages.
- We demonstrate that editorial preferences can be learned from spatial layouts. Across many domains that we test, our models achieve $> .8$ f1-score.
- We show via two case-studies – (1) newsworthiness agreement between outlets, and (2) generating newsworthiness rankings for non-news corpora – that such learned preferences can generalize beyond the corpora we study and provide useful tools for end-users.

This work opens new avenues for exploring how implicit cues in digital environments reflect latent priorities and organizational principles. By modeling these cues, we can gain richer insights into the mechanisms that influence human perception.

2 Homepages Are a Source of Preference Signals

Visual cues for editorial preferences on homepages have a deep history in the design principles of physical newspapers (Barnhurst and Nerone, 2001). At *The New York Times*, for example, top editors and designers convened daily in the renowned *Page One* meeting (Usher, 2014) to determine the most important articles for the print newspaper the next day[1]. In the digital era, meetings like this evolved into *Homepage Meetings* (Sullivan, 2016), influencing the design and content placement on the website's homepage for the upcoming day. As such, homepages continue to be distillations of professional judgement and priorities.

One visual cue editors use is **positional placement**, with articles positioned towards the top and left of a page considered more important (Nielsen, 2006). This stems from observations that readers naturally begin scanning from the top-left corner (Bucher and Schumacher, 2006). Secondly, the **space** articles occupy is considered: larger articles or headlines are perceived as more important (García, 1987). In print media, prominence is conveyed through more column space; in digital media, longer headlines, featured images, and extended summaries. Finally, **graphics and design** also play a pivotal role in signaling the importance of news stories. Articles accompanied by photographs, videos, or other multimedia elements are often deemed more significant (Zillmann et al., 2001). The use of capital letters, bold fonts, and color further enhances a story's prominence.

We find few large-scale computational analyses studying these attributes. To enable a more precise study of editorial judgement, we construct a large corpus of news homepage layouts, over which we can track these indicators of relative importance.

3 Dataset Construction

3.1 Compilation of News Homepages

We compiled a list of 3,489 news homepages, as of the time of this writing, which we scraped twice daily on an ongoing basis over a period of three years. From 2019-2024, we have collected a total of 363,340 total snapshots. Our dataset collection is actively maintained and facilitated by a large contributing community of over 35 activists, developers and journalists. We collect homepages from national news outlets (e.g., *The New York Times*, *The Wall Street Journal*), state-level news outlets (e.g., *San Francisco Chronicle*, *Miami Herald*), as well as local and subject-matter-specific news sources. Table 1 provides a sample of the different categories of news homepages included in our dataset, and a full list can be found in the appendix. Additionally, we collect homepages from

[1]Terms like "above the fold" emerged to signal story-importance (i.e. the story is above the point at which the newspaper folds, so it is seen on newsstands)

news websites of over 32 countries in 17 languages (please see Tables 6 and 8 for a more detailed breakdown). This is an ongoing and expanding effort: we encourage contributors to add their own news homepages of interest using for our suite of tools to scrape.[2] We hope to further diversify the news sources in the dataset that we collect.

3.2 Data Collection Pipeline

Our dataset collection runs in a chron job twice a day, and uploads data to Internet Archive. For each snapshot, we store the following information:

1. **All links on the page:** We store a flat-list of hyperlinks on every homepage and associated text.
2. **Full-page screenshots:** We store JPGs of each complete homepage as we render it.
3. **Complete HTML snapshots (subset of pages):** For a subset of homepages, we save a compressed version of the webpage, including all CSS files and images, using SingleFile[3].

In addition to our Internet Archive storage,[4] we also synchronize with Wayback Machine to store these homepages, providing a secondary backup and ensuring long-term preservation.

4 Dataset Processing

In order to robustly extract visual attributes for each article on a homepage (i.e. size, position, presence of graphics), we need to determine bounding boxes for all articles on a homepage. Examples of bounding boxes are shown in Figure 1: each bounding box, also referred to as *article card*, covers all information directly associated with that article.

Layout parsing is a well-researched field (Shen et al., 2021; Li et al., 2020). However, homepages present unique challenges due to their diverse structures: text of varying size, fonts, colors and images are easily perceived by humans. Because none of the largest supervised datasets (Zhong et al., 2019) are specific to our task, we find that existing resources fail for parsing homepages. So, we bootstrap a supervised detection task.

4.1 Bootstrapping a Bounding Box Detector

Following other bootstrapping approaches (Amini et al., 2022), we: (1) develop a simple deterministic algorithm to generate candidate data, (2) apply a filtering step to exclude low-quality data, (3) use our high-precision dataset to train a more robust classifier. Figure 7, in the Appendix, provides an overview of the pipeline.

Step 1: Find Bounding Boxes Deterministically We design a deterministic algorithm, called the DOM-Tree algorithm, to start our bootstrapping process. At a high level, the algorithm traces each <a> tag in the Document Object Model (DOM) and extracts the largest subtree in the DOM that contains *only a single* <a> *tag* (illustrated in Figure 4, Appendix). This method can extract the maximal bounding box for each article, however it faces robustness challenges, for example, if a link exists *within* an article card (e.g. a link to an authors page, as shown in Figure 4b, Appendix.) We apply this algorithm to a subset of the NewsHomepages dataset, combining 15 homepages each from all outlets for which we have HTML files, JPEG snapshots, and hyperlink json files (approximately 15,000 homepages). Since each outlet typically maintains a consistent layout on their homepages across samples, we include more outlets for generalizability.

Step 2: Filter Low-Quality Bounding Box Extractions We take several filtering steps to prevent "drift" (Amini et al., 2022). (1) First, we exclude non-news article links (e.g. log-in pages) by training simple text classifier to distinguish between URLs to news articles and others. We manually labeled over 2,000 URLs. The model achieves an accuracy of 96%. (2) Then, we exclude bounding boxes that did not overlap highly with link text. We determine this by first rendering the HTML pages as images and overlaying bounding boxes, then running OCR to extract the bounding-box text. (3) Finally, we exclude bounding boxes with improperly rendered images[5]. To address this, we again rendered HTML pages as an image and employed the YOLO object detection model (Redmon and Farhadi, 2018) to compare these images to the JPEGs in our archive. If a screenshot was not within 80% of the detection count of the archived snapshot, we discarded the snapshot. Overall, this multi-stage filtering process significantly reduced the number of boxes that did not correspond to actual articles and removed many websites that

[2] For more information on how to contribute, please see: https://github.com/palewire/news-homepages. For all code and data associated with this project, see https://github.com/alex2awesome/homepage-newsworthiness-with-internet-archive.

[3] https://github.com/gildas-lormeau/SingleFile, incidentally the same software that Zotero uses. In initial experimentation, we observed that capturing complete, compressed HTML snapshots was far more robust than capturing assets

[4] https://archive.org/details/news-homepages

[5] Likely due to errors in HTML extraction or dead links

Category	Example Outlets
National	The New York Times, The Wall Street Journal, NPR, Bloomberg
State-level	San Francisco Chronicle, Miami Herald, Chicago Tribune
Local	Sturgis-Journal, The Daily Jeffersonian, LAist, The Desert Sun
Subject-specific	The Weather Channel, Chessbase, ESPN
International	India Today, Ukrinform, BBC, Prensa Grafica, Japan Times

Table 1: Sample of News Homepages by Category

		FP#1	FP #2	FN #1	FN #2	Total Errors	% Correct
Challenge dataset	DOM-Tree algorithm	117	137	127	265	646	61.3%
	Detectron2 Model	25	23	27	87	162	90.3%
Clean dataset	DOM-Tree algorithm	12	20	0	13	45	97.1%
	Detectron2 Model	15	24	0	18	57	96.3%

Table 2: Error analysis of bounding box detection methods comparing the DOM-Tree algorithm and a Detectron2 model across two datasets: the challenge dataset and the clean dataset. The challenge dataset is formed by selecting the bottom 10% of articles based on the match between OCR-extracted text and retrieved link text (described in Section 4 Step 2), while the clean dataset contains well-matched articles. Error types are divided into false positives (FP #1: multiple articles in one box, FP #2: no articles in a box) and false negatives (FN #1: partially captured articles, FN #2: articles not captured). As can be seen, the our trained model performs at par on the DOM-Tree algorithm in the clean settings and is far more robust in noisy settings.

contained broken or corrupt data, enhancing the quality of the training data.

Step 3: Train a Robust Classifier Now with our dataset in hand, we trained a Detectron2 model (Wu et al., 2019). Our model uses ResNet-101 as a backbone with a Feature Pyramid Network (FPN) for extracting multi-scale features and Smooth L1 loss for bounding box regression. During training, we used a base learning rate of 0.02 with a linear warmup over the first 1000 steps. We trained the model for 10,000 steps in total, with learning rate reductions after 5000 steps. A weight decay of 0.0001 and momentum of 0.9 were also employed. The training ran on 4×A40 GPUs for 24 hours.

4.2 Evaluation and Results

To evaluate the quality of our bounding box detection, we conducted manual validation for four types of errors: 1) bounding boxes that contain multiple articles, 2) bounding boxes that contain no articles, 3) bounding boxes missing parts of an article, and 4) articles that are note captured.

We used the OCR text-matching method, as described in Section 4, to identify particularly challenging homepages.[6] We compared errors on the cleanest 10% of homepages (Clean) and the least-clean 10% (Challenge). As shown in Table 2, our computer vision model (Detectron2) significantly improved the accuracy of bounding box detection in contexts where the DOM-Tree algorithm struggles (the Detectron2 model had an Card Correct % score of 90.3% while the DOM-Tree had a score of 61.3%). For Clean pages, the Detectron2 model performed similarly to the DOM-Tree algorithm, with error differences being minimal and both models achieving high accuracy (above 96%). The combination of deterministic algorithms and machine learning techniques allow us to achieve a more robust extraction of article attributes from diverse homepage layouts.

5 Preference Modeling

Given precise layout information for the 363k homepages in our dataset, we arrive again at the core question of this research: how regular and predictable are the preferences expressed in an outlet's layout decisions? We initially hypothesized that modeling homepage placement would be challenging. As shown in Figures 3, 5, 6[7] and described by (Angèle, 2020), certain areas of many homepages lack clear editorial consistency. This introduces noise and makes it difficult to learn a uniform policy guiding article placement decisions. Further, learning a single set of policies is challenged by the changing news cycle; some days have lots of news while others have less.

5.1 Modeling Approach

A homepage is intended to present a collection of articles as a cohesive bundle; individual articles do not exist in isolation (Tufte, 1990). Predicting the placement of a single article without considering the context of other articles would be overly noisy and potentially ineffective (Salganik et al., 2006).

[6] Figure 8, in the Appendix, demonstrates the resulting histogram for the distribution of OCR-match scores across our dataset.

[7] In Appendix B

Model Name	Size			Position x Size			Position		
	F1	**Precision**	**Recall**	**F1**	**Precision**	**Recall**	**F1**	**Precision**	**Recall**
Flan-t5-base	91.9	91.8	92.0	70.7	80.5	63.1	64.5	79.0	54.5
Flan-t5-Large	66.6	51.1	95.4	54.9	43.4	74.7	34.5	42.7	29.0
Roberta Base	91.0	91.7	90.4	64.9	78.1	55.6	37.3	69.3	25.5
Roberta Large	85.4	85.9	84.9	47.2	74.4	34.6	49.3	56.1	43.9
Distilbert-Base-Uncased	93.1	93.3	92.9	75.2	81.8	69.6	70.1	79.5	62.7

Table 3: Performance metrics on NYTimes data for different models

Outlet	Accuracy	F1	Recall	Prec.
phoenixluc	57.1	70.3	57.4	90.7
newsobserver	75.0	72.5	74.3	70.7
slate	72.4	61.6	66.2	57.7
jaxdotcom	75.2	63.4	65.5	61.4
arstechnica	64.7	17.5	41.4	11.1
airwaysmagazine	72.5	73.7	78.9	69.1
denverpost	73.7	67.8	70.5	65.4
thedailyclimate	82.0	80.9	81.3	80.6
breitbartnews	68.9	22.8	54.7	14.4
foxnews	67.3	38.6	55.6	29.5
motherjones	71.4	63.0	68.7	58.2
thehill	68.8	55.5	59.8	51.7
wsj	70.0	48.0	52.0	44.6

Table 4: Performance metrics on a sampling of outlets, including on ones we used for the downstream experiments in Section 6. Done with Distilbert-Base-Uncased model trained on position x size cues.

Conversely, attempting to predict the placement of all articles simultaneously poses a combinatorial challenge that is computationally infeasible.

To address this issue, we formulate our modeling task as a pairwise preference problem. Specifically, we consider pairs of articles (a_1, a_2) and train models to predict a binary preference variable p, where $p_o(a_1 > a_2) = 1$ if article a_1 is preferred over article a_2 for outlet o, and $p_o(a_1 > a_2) = 0$ otherwise.

We explore three variations of preference criteria for the preference variable, p, to create weak labels:

1. **Size-based Preference**: We define $p_o(a_1 > a_2) = 1$ if article a_1 occupies more surface area on the homepage than article a_2, assuming that prominent articles are given more space (Lambert and Brock, 2005).
2. **Position-based Preference**: We set $p_o(a_1 > a_2) = 1$ if article a_1 is placed in a more favorable location on the homepage than article a_2, such as higher up or more to the left, based on common reading patterns (Nielsen and Pernice, 2009).
3. **Combined Size and Position Preference**: Here, $p_o(a_1 > a_2) = 1$ if article a_1 either occupies more surface area or is in a more favorable position than article a_2, particularly focusing on articles that are in the top 10

To model these preference variables, p, we train a simple Transformer-based binary classifier, `distilbert-base(X)`, which classifies a text sequence X. Our model concatenates the input articles: `X=a1<sep>a2` as input; the model learns to recognize the `<sep>` token as a boundary between the first and the second articles.

5.2 Modeling Variations

We explored different modeling variations on the *New York Times* homepages, as they have a variety of content, shares and functionalities on their site (Spangher, 2015). We test 5 different models: {distilbert-base-uncased, flan-t5-base, flan-t5-large, roberta-base, roberta-large} and constructed a training dataset of 74,857 article-pairs and a test dataset consisting of 18,715 datapoints consisting of pairs of NYTimes articles from same homepages.

We experienced exploding gradients in the flan-t5-large and RoBERTa-large models, motivating us to use a learning rate limit of 5e-5 for all the models, for the sake of equal comparison. We applied Parameter-Efficient-Fine-Tuning (Mangrulkar et al., 2022) on flan-t5-base, flan-t5-large, roberta-base, roberta-large models to minimize overfitting, as we had limited of datapoints.

The distilbert-base-uncased model outperforms other models (Table 3). We trained on 4xA40 GPUs and 16xA100 GPUs, and implemented gradient clipping after observing gradient explosion.

5.3 Dataset Selection and Processing

From our list of 3,000 outlets, we select 31 outlets for detailed analysis. We selected well-known outlets in various categories, including different political leanings (left-leaning vs. right-leaning[8]), local and national levels, and varied subject matters such as science, chess and aviation. For each outlet, we collected between 200 and 300 homepage snapshots, resulting in 1,000 to 50,000 pairs of articles. We created an 80/20 train/test split and trained distilbert-base-uncased models for each outlet. We trained each model with 5e-5 learning rate limit, 3 epochs, 0.01 weight decay.

Each article in our dataset includes its textual representation as it appeared on the homepage. To enhance the reliability of our models, we undertake

[8] As classified by MediaBiasFactCheck.com

several data processing steps informed by preliminary experiments: (1) we only sample pairs of articles that are adjacent on the homepage, to curate preference pairs that are more likely to be challenging and topically similar. Secondly, we clean the textual representations by stripping out any times, dates, and formatting elements. We also remove author names to prevent the models from learning biases based on authors who might be favored by the organization. Please refer to Appendix A for a detailed list of the outlets used and the specific number of data points associated with each.

5.4 Results

We show our results in Table 4. While some models (e.g. `Breitbart`) perform noticeably poorly, we note that the majority of our models score above $f_1 > .6$. We do not find a significant correlation between model performance and training set size. We were surprised to observe the tractability of this task; this indicates that many of the concerns we had about noise were either handled by our preprocessing steps, or not as important as we believed.

6 Demonstrations

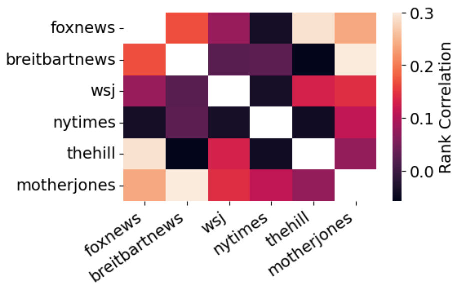
To evaluate the practical utility of our models, we design two downstream tasks: (1) analyzing newsworthiness agreement between publishers, and (2) using newsworthiness models to rank corpora of interest to journalists.

6.1 Task 1: Newsworthiness Agreement Between Publishers

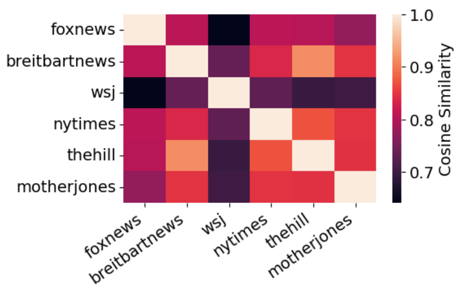
In this task, we aim to rank-order lists of news items drawn from a larger pool of articles to calculate the agreement rates for newsworthiness decisions between different news outlets. Previous research has observed surprising overlaps in sentiment and preferences between right-leaning and left-leaning outlets (Gentzkow and Shapiro, 2010), and we wish to quantitatively test this phenomenon using our preference models.

We selected 9 of the 31 outlets for which we trained preference models in the previous section. From each outlet, we sampled 1,000 articles, matching on variables such as topic, length, publication date, and other potential confounders. These 9 outlets were chosen because they represent a range of political viewpoints.

For each model n_{o_i} (corresponding to outlet o_i), we used it to sort lists of 1,000 articles $\{a_1, a_2, \ldots, a_{1000}\}_{j=1}^{9}$ from outlets $\{o\}_{j=1}^{9}$. In other words, the output of applying model n_{o_i} to



(a) Kendall's τ correlation between the newsworthiness preferences expressed by preference models trained on different news outlets.



(b) Cosine distance of average SBERT similarity between articles sampled from each outlet.

Figure 2: Comparison of Kendall's τ rank correlation (on newsworthiness judgements) and SBERT cosine similarity (on articles) across news outlets.

the article list from outlet o_j is a fully sorted list $n_{o_i}(A_j)$. We used the size $\times$ position model for this experiment, as performance was similar to the size-only model, and we believed that the multi-variable models capture more newsworthiness information than the single-variable models.

We calculated Kendall's τ, a correlation measure for ordinal data, between each pair of sorted lists $(n_{o_i}(A_k), n_{o_j}(A_k))$ for all i, j, k, and averaged the correlations across j. The resulting correlation matrix is displayed in Figure 2a. Some surprising insights emerge from this analysis. Notably, *Breitbart*, a right-leaning outlet, and *Mother Jones*, a left-leaning outlet, have one of the highest rates of agreement.

To establish a baseline and ensure we are not merely capturing topic overlap (despite matching on topics), we conducted a simple SBERT embedding experiment (Reimers and Gurevych, 2019). We sampled a set of 100 articles per outlet, generated embeddings using SBERT, and averaged these embeddings to create single outlet-level embeddings, as shown in Figure 2b. These embedding-level similarities align more closely with topical overlaps, indicating distinct right-wing and left-wing clusters with some overlap in between.

Taken together, these results suggest that newsworthiness preference is a compelling and orthogonal variable for study beyond topical similarity.

6.2 Task 2: Surfacing Newsworthy Leads

In this task, we explore how well these newsworthiness judgments transfer outside of the news domain. In this task, we build on the work of Spangher et al. (2023). The authors introduced the task of *newsworthiness prediction* as a detection and alerting system for journalists: utilizing a list of San Francisco Board of Supervisors' policies (a typical source of stories for journalists), they attempted to detect which policies were *more newsworthy* in order to alert journalists.

Here, we suspect that editorial cues from different homepages will help us surface especially newsworthy content based on the preferences of each outlet. We applied the models from each outlet to sort the list of Board of Supervisors' policies. Then, we selected the top 10 items from the ordered lists n_{o_i} and used a large language model (LLM) to summarize the key points raised in each policy.[9]

The LLM's summarization results and examples are shown in Table 5. Themes emerge, with subject-specific outlets like *The Weather Channel* highlighting policies related to environmental issues. We presented these results to a group of journalists, and 81% of respondents indicated they were impressed and would consider using such a system in their workflow. These findings demonstrate the potential of our models to assist journalists in identifying newsworthy leads from large corpora of documents, thereby supporting investigative journalism and timely reporting.

7 Discussion

Our demonstrations show two core findings: first, editorial priorities and decision-making can be inferred simply by examining the layout decisions made on homepages. This decision-making is distinct from simple topic preferences, as we show. In fact, commonalities about decision-making can be observed between outlets that appear distinct topically. Second, newsworthiness judgements have potential to be used in tools for reporting.

Stepping back, these results indicate that homepage editorial cues provide an interesting, novel angle for news analysis, as well as a tantalizing direction in newsworthiness detection (Spangher et al., 2023; Diakopoulos et al., 2010). Both of these applications are premised by the assumption that editorial cues learned from one outlet's homepage can be transferred to other domains, be it *another* outlet's articles, or non-news content. This is an important assumption: the intuitive findings that we have made in our demonstrations provide some degree of proof that this transfer is robust.

We experimented with different ways of making this transfer even more robust. We attempted to train *additional* models to serve as in-domain and out-of-domain classifiers, and then multiplied the probabilities: $\hat{P}_o(a_1 > a_2) = p_o(in\_domain|a_1, a_2) \times p_o(a_1 > a_2)$, where for outlet o, $p_o(in\_domain|a_1, a_2) = 1$ if a_1 belongs to o while a_2 does not. However, our results in this direction were not more interpretable than the results we reported. Ultimately, without any "gold truth" about how an editor from outlet o would rank an arbitrary list of strings, we will not have a conclusive measurement about our ability to replicate these measurements. In order to fully validate our observations, this appears necessary. Our results have to be taken with some important further caveats. While some newsworthiness models were impressively well-performing, many were not. Further exploration is needed to determine the causes. Additionally, despite the presence of non-English homepages in our dataset, we only tested with U.S.-based websites. We look forward to continuing to expand this work to address these concerns.

With these caveats in mind, we hesitate to draw firm conclusions. However, we feel the results of our modeling are encouraging enough to continue to address these concerns and run further manual experiments with editors. We imagine a future where editorial preferences made by professional editors can be used to routinely study importance and organization of content. We imagine insights being applied more broadly to build tools for journalists, improve webpage layouts that are currently automated, and even understand more fundamental components of the human psyche.

8 Related Work

Prior research on *newsworthiness* underscores the role of editorial gatekeepers in selecting and emphasizing stories that align with certain values and organizational objectives (Galtung and Ruge, 1965; Harcup and O'Neill, 2001, 2017; Shoemaker, 1991; Herman and Chomsky, 2021). These studies highlight factors like timeliness and unexpectedness in shaping editorial choices, providing theoretical foundations for understanding news organizations' preferences. Our work extends these perspectives

[9] We used GPT-4 for this experiment.

Outlet	Top Policies LLM Summaries	Examples of Policies
Weather Channel	Environmental Policies, Public Health and Emergency Response, Infrastructure and Development	Reducing nutrient pollution from wastewater; Accepting grants for forensic science improvements
Daily Climate	Environmental and Energy Policies, Urban Planning and Development	Agreement with North Star Solar; Building code enforcement
Fox News	Community and Public Safety Policy, Education and Social Policy, Fiscal and Economic Policy	Appointment of individuals to advisory committees; Appropriating funds for San Francisco Unified School District; Developing materials on domestic violence
Mother Jones	Social Policies, Environmental and Health Policies	Sanctuary City Protection; Urging Pardons; Edible Food Recovery and Organic Waste Collection
Ars Technica	Infrastructure Policies	System Impact Mitigation Agreement; 6th St. Substation
NYTimes	Social & Cultural Awareness Policies, Labor & Employment, Economic, Housing policies	Commemorative and Awareness Events; Labor Dispute Hearings; Affordable Housing Loans
WSJ	Economic and Infrastructure Policies, Governance and Legislative Policies	Contract modifications; Bond sales; Ground lease agreements; Charter amendments concerning commissions and departments related to aging and adult services

Table 5: Summaries of the top 10 most newsworthy policies published by the San Francisco Board of Supervisors, as ranked by models trained on 7 different homepages.

by examining how such judgments manifest in homepage layouts, offering a large-scale computational lens on editorial decision-making.

Visual cues, such as headline size, article position, and images, significantly influence how readers perceive the importance of news stories (Brooks and Pinson, 2022; Nass and Mason, 1990; Nielsen and Pernice, 2009; Bucher and Schumacher, 2006). Building on eye-tracking evidence that indicates a top-left viewing bias, researchers have proposed computational frameworks to model how layouts guide attention. We incorporate these findings by focusing on spatial arrangement as a measurable signal of prioritization, demonstrating that visual structure itself encodes editorial judgments.

Data-driven investigations into media bias and agenda-setting have traditionally centered on textual analysis (Gentzkow and Shapiro, 2010; Roberts et al., 2021; Misra, 2022; Silcock et al., 2024; Leetaru and Schrodt, 2013; Spangher et al., 2022), whereas emerging research leverages algorithms to support journalistic decision-making (Arya and Dwivedi, 2016; Diakopoulos et al., 2010). In contrast, our work examines how homepage layout attributes can be used to infer editorial preferences, linking presentation-driven signals with broader patterns of newsworthiness. This approach not only complements existing bias and recommendation studies but also opens pathways for new tools to help editors and developers refine news curation strategies.

9 Conclusion

This work introduces NewsHomepages, a large-scale dataset and modeling framework to study editorial prioritization through homepage layouts. By leveraging weakly supervised learning, we show that the spatial arrangement of news articles can be treated as implicit preference signals, akin to how community upvotes are used to train preference models in RLHF (Ouyang et al., 2022; Bai et al., 2022). Our results demonstrate that homepage layouts are a viable source of rich, interpretable signals about editorial priorities, achieving over 0.8 F1 scores in most cases. This computational approach provides a new lens for understanding how media organizations organize information and offers a generalizable method for learning from visual cues.

Our demonstrations highlight two key contributions. First, we show that editorial judgments reflected in homepage layouts can generalize beyond the domains where they are learned. Our models not only capture patterns of prioritization within a single outlet but also transfer across different outlets and even non-news contexts, such as ranking government policy documents. Second, we establish that editorial decisions, while diverse across outlets, exhibit surprising commonalities. For example, the prioritization preferences of *Breitbart* and *Mother Jones*—outlets that differ ideologically—are more similar than expected. These findings offer new directions for studying editorial decision-making, content bias, and agenda-setting.

We leave to future work the incorporation of these cues into language modeling objectives. We hope this work inspires further exploration of how layout-based cues reflect the latent priorities of media organizations and how these cues can be leveraged for automated content curation, personalized news delivery, and broader social science inquiries into human attention and information design.

10 Limitations

This work, while advancing the study of editorial prioritization on homepages, comes with several limitations. First, the dataset, although large and diverse, predominantly focuses on English-language news outlets from the U.S., which may limit the generalizability of our models to international or non-English outlets. Despite the inclusion of some non-U.S. and non-English homepages, the models have not been explicitly evaluated on a broader range of languages or cultural contexts. This focus may overlook regional editorial conventions and biases that differ significantly from the U.S. context.

Another limitation is that the study focuses primarily on visual cues of newsworthiness, such as size, position, and graphical elements. While these cues are significant, they are not the only factors that influence editorial decisions. The models do not account for less visible but equally critical considerations, such as journalistic ethics, editorial mandates, or audience engagement metrics, which may influence homepage layouts but remain unquantified in this dataset.

Additionally, the weakly-supervised learning methods employed for layout parsing may struggle with more complex or irregular homepage designs. As described, the model had trouble generalizing to homepages with obscure HTML structures, leading to imperfect bounding box detections in some cases. This could result in misinterpretations of editorial significance, especially for websites with non-traditional or highly dynamic layouts.

Lastly, the results may have some bias due to the reliance on pairwise article comparisons. This method, while efficient, reduces the complexity of editorial decision-making into binary relationships, potentially overlooking more nuanced or multifaceted prioritization strategies that editors use in practice.

10.1 Computational Budget

The computational resources required for this project were substantial. The model training involved 4×A40 GPUs for initial phases and 16×A100 GPUs for more extensive model fine-tuning and deployment. Training the custom Detectron2 model alone took 24 hours, with additional time required for fine-tuning and model testing across multiple outlets. While the experiments could be completed within this budget, more extensive experiments across all 3,000 outlets would require significantly more resources, especially when scaling to different languages and regional variations.

10.2 Use of Annotators

The dataset used in this work was primarily compiled automatically through web scraping, with minimal manual annotation. However, annotators were employed to manually label URLs to distinguish between news articles and non-news articles during the preprocessing phase. A set of 2,000 URLs was manually labeled, contributing to a more refined and accurate dataset. The authors performed this task themselves. However, beyond this, no human annotators were used to manually assess newsworthiness, as the models relied on position and size as proxies for editorial decisions.

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Language	Count
English	975
Spanish, Castilian	44
Portuguese	36
Nepali	24
French	21
German	10
Japanese	9
Norwegian	8
Hindi	7
Hebrew	7
Russian	7
Italian	5
Ukrainian	5
Chinese	3
Afrikaans	3
Zulu	2
Xhosa	1

Table 6: Our corpus comprises homepages from 18 different languages. We assign each news outlet to the language of the majority of it's articles' languages (e.g. the *New York Times* sometimes publishes Spanish-language articles, but is predominantly and English-language newspaper).

A Dataset Details

In this section, we present more detailed dataset statistics. In Table 6, we show the different languages collected in our corpora and in Table 8 we show

'ainonline, airwaysmagazine, arstechnica, bleacherreport, breitbartnews, chessbase, cnet, denverpost, foxnews, jaxdotcom, jessicavalenti, jezebel, motherjones, newsobserver, nytimes, phoenixluc, rollcall, seattletimes, sfchronicle, sinow, slate, startelegram, studyfindsorg, thealligator, theathletic, thedailyclimate, thehill, weatherchannel, wired, wsj, yaledailynews'

B News Homepage Layouts

In Figure 3, we show several areas of a homepage where editorial policies are likely to be unclear and challenging to model. In the top section, a "Breaking News" feed shows articles shortly after they are published. They usually do not stay long in these positions (Costanza-Chock and Rey-Mazon, 2016), so there is high variability in this section. In the middle section, a "Section Fronts" show top articles in each section, each combining the different priorities of the desks (Angèle, 2020). Finally, in this reporter's experience, the bottom of a homepage was affectionately called the "Gutter". However, it

Outlet	Domain		Position x Size	
	Train	Test	Train	Test
ainonline	2159	540	3844	962
airwaysmagazine	1233	309	1669	418
arstechnica	9349	2338	17883	4471
bleacherreport	3849	963	6689	1673
breitbartnews	7824	1957	15199	3800
chessbase	2094	524	3151	788
cnet	3769	943	6521	1631
denverpost	18802	4701	36607	9152
foxnews	62170	15543	125096	31274
jaxdotcom	4100	1026	7206	1802
jessicavalenti	455	114	512	129
jezebel	6270	1568	10956	2740
motherjones	2443	611	3572	893
newsobserver	7538	1885	14078	3520
nytimes	38432	9608	74857	18715
phoenixluc	209	53	305	77
rollcall	6572	1643	12436	3109
seattletimes	20942	5236	40882	10221
sfchronicle	5600	1401	10952	2739
sinow	176	44	315	79
slate	23527	5882	45470	11368
startelegram	11964	2992	22932	5734
studyfindsorg	450	113	403	101
thealligator	3046	762	5432	1359
theathletic	22722	5681	44463	11116
thedailyclimate	7211	1803	13688	3423
thehill	30800	7700	59965	14992
weatherchannel	4551	1138	8094	2024
wired	2058	515	3196	800
wsj	15569	3893	30496	7625
yaledailynews	1378	345	2527	632

Table 7: Size of training and test sets, in terms of # of pairs, used in our experiments.

is more commonly referred to as a "footer"[10]

We can extend this analysis by visualizing the flow of articles on a homepage over time. We show in Figure 5 where articles tend to get added and deleted overall, as well as where they stay the longest. In Figure 6, we show how articles shift frequently around a homepage.

[10] https://alyamanalhayekdesign.com/blog/the-parts-of-a-webpage-a-complete-list/

Country	Count
United States	892
Brazil	37
United Kingdom	32
Nepal	24
Canada	20
South Africa	18
France	17
Spain	13
Mexico	13
India	10
Japan	9
Argentina	9
Israel	9
Germany	9
Russia	8
Norway	8
Ukraine	6
Ireland	6
Italy	5
New Zealand	4
Austria	3
Taiwan	3
Colombia	2
Australia	2
Uruguay	1
Qatar	1
Belgium	1
Latvia	1
Bosnia and Herzegovina	1
Georgia	1
El Salvador	1
Lebanon	1

Table 8: Countries of origin for the homepages we collect, based on where the organization is based.

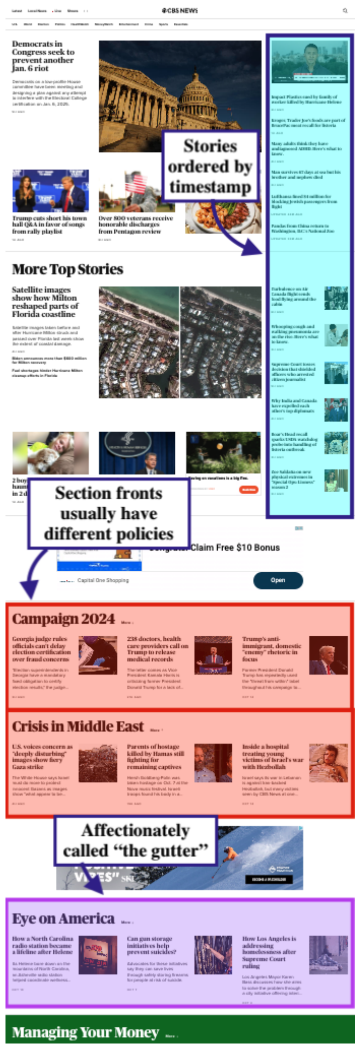
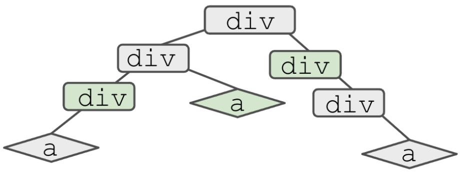


Figure 3: We show three sections of a sample homepage (from CBS News) where editorial decisions for different reasons. We highlight the “Breaking News” Section, “Section Fronts” and “The Footer”.



(a) Our deterministic algorithm starts at all $\langle a \rangle$ nodes and recursively traverses up the DOM to find maximal subtrees with one $\langle a \rangle$. Green nodes shown are article bounding boxes.

(b) Failure cases (missing text area) with the deterministic algorithm.

Figure 4: Illustration of our deterministic bootstrapping algorithm and a failure case. Here, when non-article links exist, we misunderstand the full area of an article, excluding the text below.

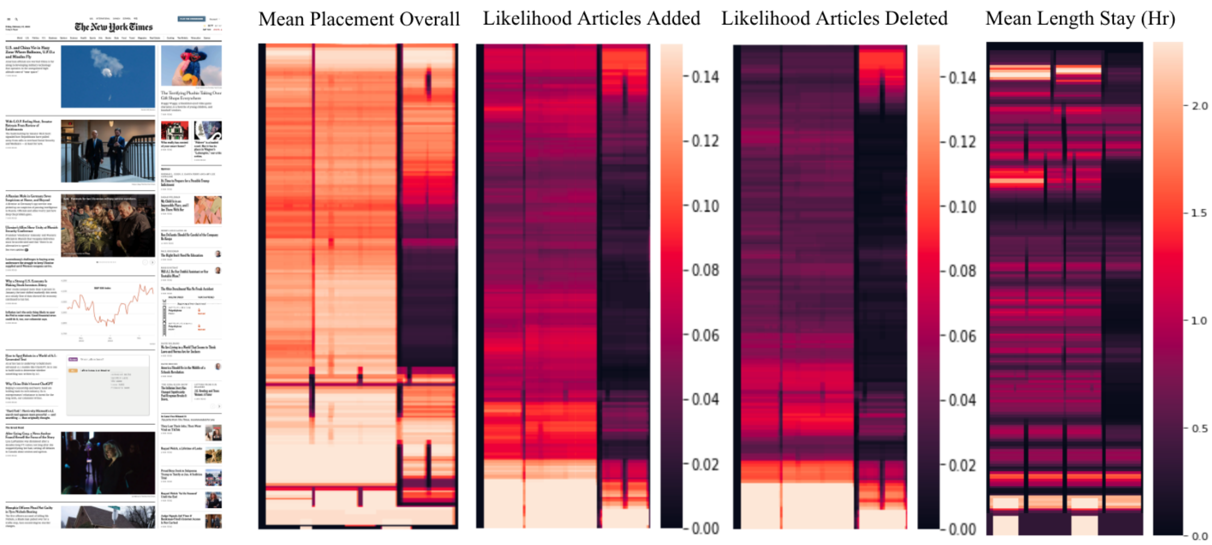


Figure 5: Different analyses we run on bounding boxes across time: average locations of bounding boxes on a homepage, locations where articles are added first, locations where they are removed, and the average time articles in various locations spend.

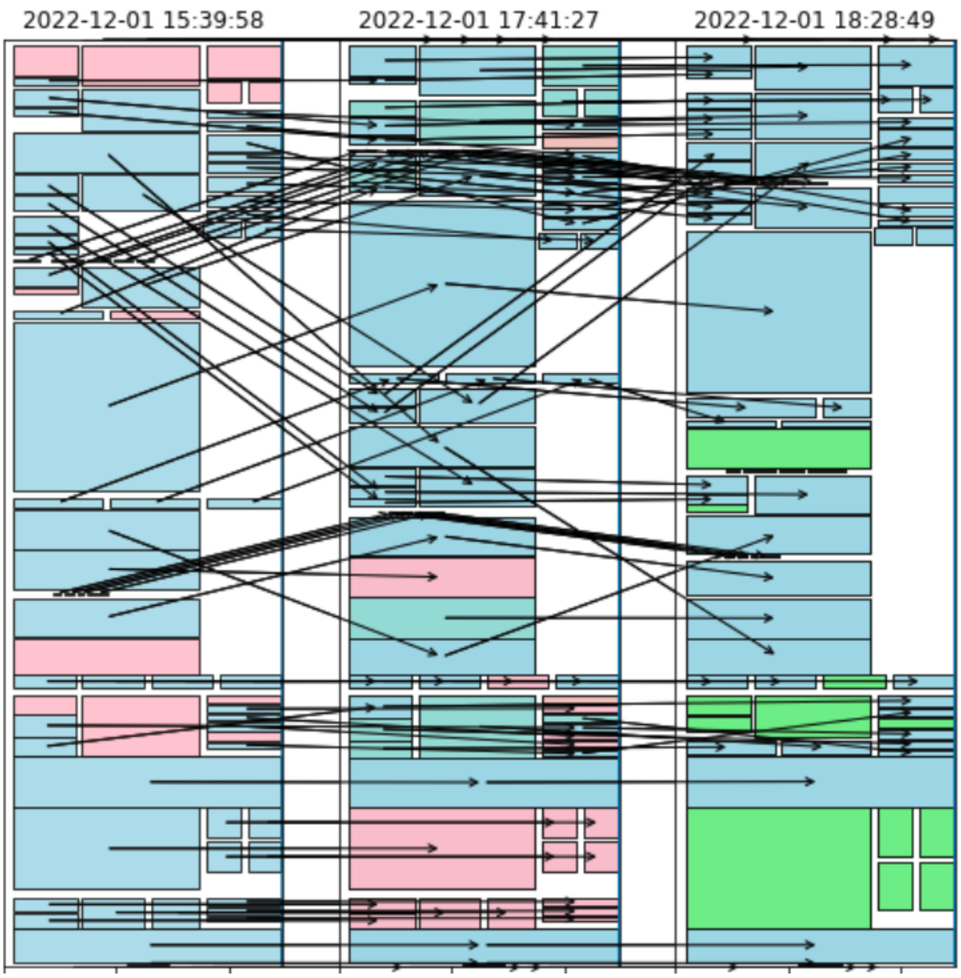


Figure 6: With our suite of tools for parsing homepages, we can examine on a granular level the movement of an article across the homepage.

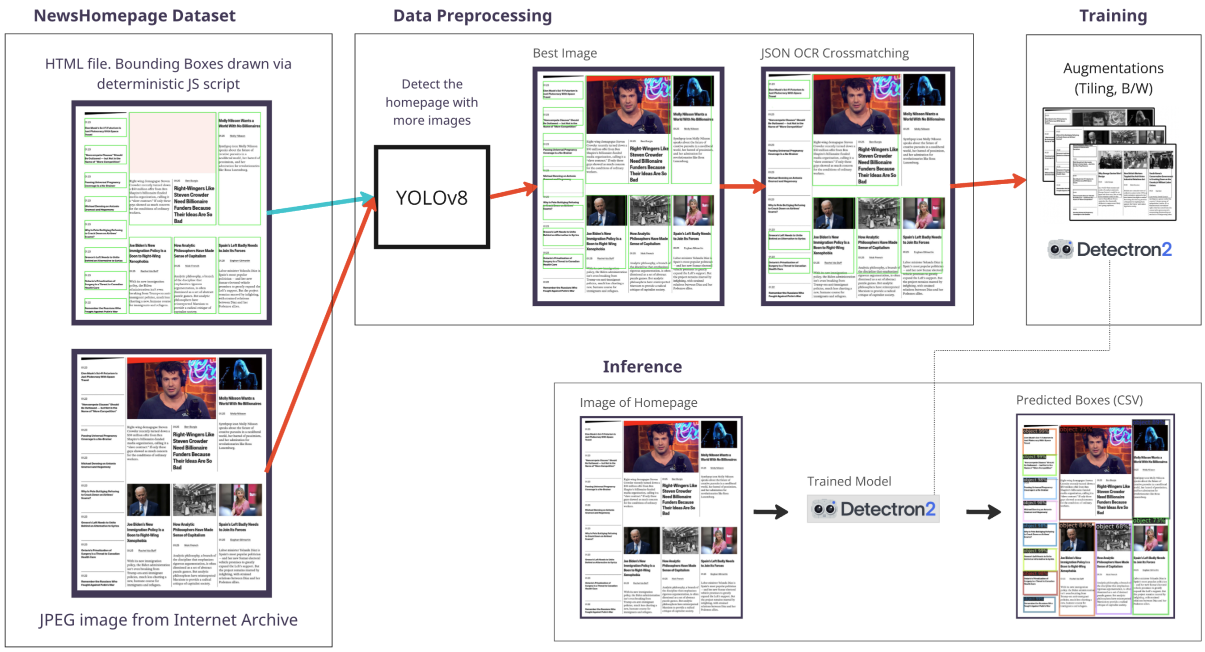


Figure 7: This diagram is an overview of the data preparation and training of the Detectron2 model for predicting bounding box on websites.

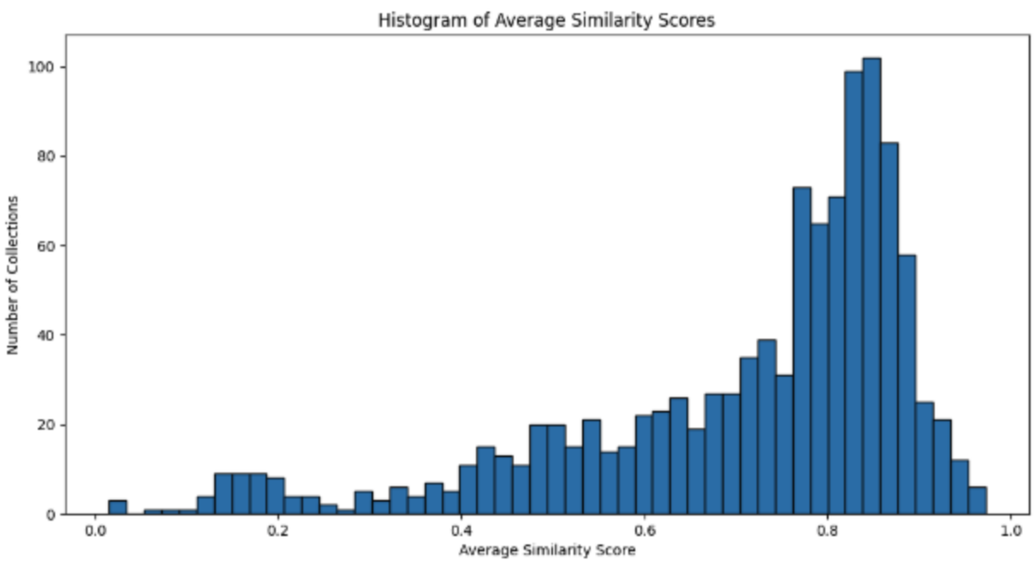


Figure 8: When sorting our sources to determine the ones most difficult for the DOM-Tree algorithm, we define the Average Similarity score to be a general measure as to how well the bounding box's text match the article's JSON file containing text/link pairs. High similarity score means high bounding box accuracy, and vice versa.