WebQuality: A Large-scale Multi-modal Web Page Quality Assessment Dataset with Multiple Scoring Dimensions

Anonymous ACL submission

Abstract

The assessment of web page quality plays a critical role in a range of downstream applications, yet there is a notable absence of datasets for the evaluation of web page quality. This research presents the pioneering task of web page quality assessment and introduces the first comprehensive, multi-modal Chinese dataset named ***WebQuality*** specifically designed for this task. The dataset includes over 65,000 detailed annotations spanning four sub-dimensions and incorporates elements such as HTML+CSS, text, and visual screenshot, facilitating in-depth modeling and assessment of web page quality. We performed evaluations using a variety of baseline models to demonstrate the complexity of the task. Additionally, we propose ***Hydra***, an integrated multi-modal analysis model, and rigorously assess its performance and limitations through extensive ablation studies. To advance the field of web quality assessment, we offer unrestricted access to our dataset and codebase for the research community, available at url-is-hidden-for-blind-review.

1 Introduction

As web page serves as carriers of diverse and vast knowledge, selecting superior ones facilitates more effective knowledge acquisition. Current research for web page knowledge acquisition predominantly focuses on the relevance of web content (Xie et al., 2023; Singh and Joachims, 2019), often neglecting the aspect of web page quality. The presence of low-quality web page data can significantly deteriorate user experiences (Olsina et al., 2006) in industrial applications and compromise the performance of computational models (Marion et al., 2023) in scientific research. Identifying and filtering out low-quality content from the vast array of web data, to prioritize high-quality information, becomes an urgent issue. In response to our survey indicating a lack of open-source web page quality datasets, we introduce the first dataset capable of training a quality model for web page quality assessment.

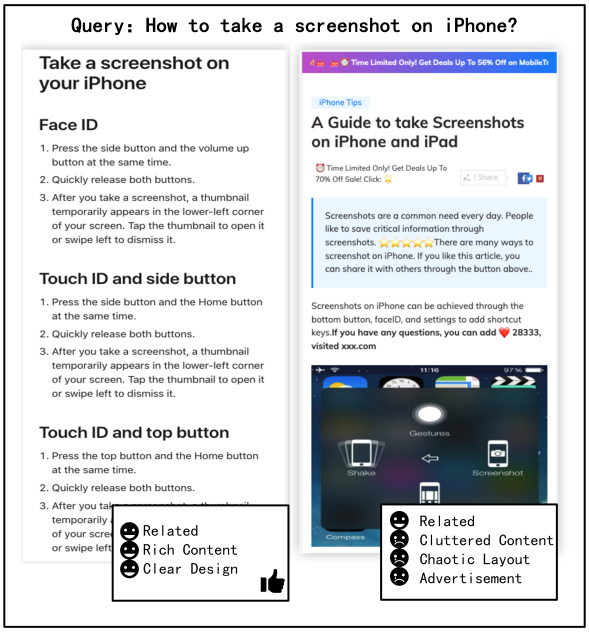
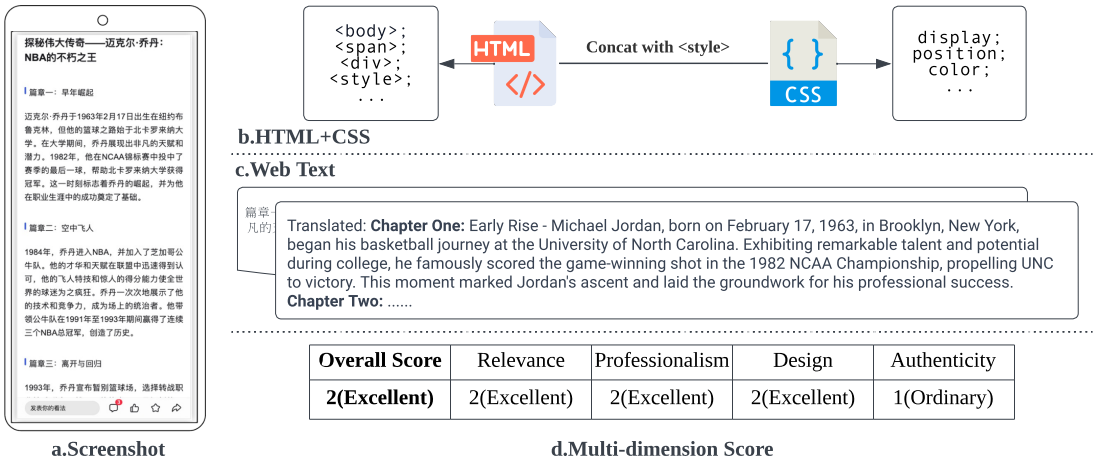


Figure 1: Comparison between high-quality and low-quality web pages.

This paper proposes a dataset for web page quality assessment, acknowledging the complexity and multi-dimensionality of the task. The evaluation process is complicated by the diversity of web pages from various sources, requiring distinct evaluation criteria. Further complexity arises from the subjective nature of quality assessments and the need for a universally applicable standard. Furthermore, as web pages are dynamic and constantly changing, we aim to preserve static web page data to ensure consistency in annotations. Against this backdrop, the paper addresses two fundamental challenges in web page quality assessment.

Q1: How to reasonably evaluate the quality of web pages?

The domain of quality assessment in web content has been extensively explored. The Automated Essay Scoring task (Ke and Ng, 2019) represents a seminal NLU endeavor, emphasizing article-level



Overall Score	Relevance	Professionalism	Design	Authenticity
2(Excellent)	2(Excellent)	2(Excellent)	2(Excellent)	1(Ordinary)

Figure 2: Input Data for Our Three Modalities with Scores for Four Sub-dimensions and Overall Score: We insert CSS styles into HTML using <style> tags, extract key textual information, and capture screenshots of the primary content on web pages. For the scoring dimensions, relevance evaluates the degree of match between content and title, professionalism assesses the expertise of the content, design examines the website's overall layout, and authenticity checks the credibility of the website.

content evaluation across dimensions such as fluency and language (Mathias et al., 2018). In the context of web quality, Anderka (2013) categorize wiki scoring into five distinct classes, albeit with a primary focus on text. Conversely, Cheng et al. (2023) prioritize the layout aspect of web pages, valuing clarity in task layout and logical structuring. However, all of above studies predominantly focus on the quality of a single modality, ignoring other modalities. As illustrated in Figure 1, even a web page meeting thematic relevance criteria can be perceived as less authentic or useful due to terrible design and advertisement. Therefore, a multi-dimensional scoring criteria is required to degrade subjectivity maximally.

Q2: How can web page quality be modeled more comprehensively?

Significant strides have been made in web page modeling. He et al. (2022) employed full-text processing to derive a final score, while Xu et al. (2020) utilized both images and text. The WebSRC dataset (Chen et al., 2021), though incorporating HTML and images, is tailored for QA tasks and does not wholly represent a web page through HTML alone. Cheng et al. (2023) consider layout aspects critical for user experience in their web page quality assessment, applicable in search engine results. Acknowledging the diverse and dynamic nature of web page layouts, we introduce a novel multi-modal dataset encompassing screenshot, text, and HTML+CSS. This dataset aims to capture the full spectrum of web page information, ensuring both diversity and consistency in representation.

In an effort to enhance the broad utilization of web page data, we have defined, for the first time, a comprehensive web page quality assessment task. We introduce ***WebQuality***, a novel large-scale, multi-modal web page quality assessment dataset collected from open resources. This dataset comprises 65,442 meticulously annotated samples across 26 web page categories, with extensive details provided in Section 3. It incorporates a four-sub-dimensional evaluation system for each page, offering comprehensive scoring and annotations. The dataset amalgamates distinct data modalities: HTML+CSS, text and screenshot, each contributing synergistically, where text delivers the web page's essential content, HTML and CSS outline its complete structure with CSS detailing style and layout, and screenshot provide a direct user experience perspective. This integrative modal approach is crucial for enhanced and thorough modeling, understanding, and evaluation of web page quality.

The contributions of our work are succinctly outlined as follows:

- We conceptualize the task of web page quality assessment, employing a multi-dimensional modeling framework that is readily extensible.
- We introduce ***WebQuality***, a novel, large-scale, open-source dataset for web page quality assessment, which facilitates a more holis-

tic approach to web page quality modeling and evaluation.

- We propose the ***Hydra*** model, amalgamating multiple modalities, thereby substantiating the viability of multi-dimensional modeling and assessment in quality evaluation, and offering valuable perspectives for downstream task research.

2 Dataset Construction

2.1 Task Formulation

2.1.1 Multi-modal Web Quality Assessment

Let x be the main content of a web page, i represent the screenshot of the web page, d the HTML dom file, and $\mathbf{s}$ denote the score of the overall page in multiple dimensions. The purpose of the task is to train a model F to predict the score of a web page.

$$F(x, i, d) = \mathbf{s} \tag{1}$$

2.1.2 Scoring Dimension Selection

In light of the inherent subjectivity in annotators' scoring (Rottger et al., 2022) and its inherent complexity (Ferrara et al., 2014), we advocate for dimension-specific annotation to mitigate these concerns. Enhanced dimensional clarity bolsters the interpretability of the resultant quality metrics. Numerous datasets for essay evaluation have embraced multi-criteria scoring (Ridley et al., 2021; Mathias et al., 2018) for comprehensive article appraisal. Given these considerations, we delineate our scoring across four bespoke dimensions for web pages:

Relevance This metric gauges content alignment with the topic and its extrapolated value. Optimal web content adheres to its theme, mirroring user prerequisites (Zhang et al., 2018). An expansion on the main topic can satiate user curiosity.

Professionalism This criterion examines the content's depth, precision, fluency, and utility. High-caliber, fluent content minimizes reader cognitive load and imparts substantial insights (Liao et al., 2021).

Design This facet assesses the aesthetic and usability of the web page. The layout's effectiveness bears significant impact on user engagement (Gardner, 2011).

Authenticity This aspect scrutinizes originality, vigilantly avoiding practices like keyword overuse or content duplication. Notably, it operates on a binary scale, given that deceptive tactics gravely mar user experience.

Refer to Table 1 for a detailed exposition of the aforementioned dimensions. Excluding authenticity, each dimension possesses a tripartite scoring gradient. Alongside these dimensional scores, we furnish an aggregate score to encapsulate the web page's holistic quality.

2.2 Data Collection

The search engine accumulates millions of queries with billions of web documents returned per day. Through a probabilistic sampling of websites accessed by users via search results over the preceding annum, we've enhanced the diversity of sites, encompassing a spectrum from subpar to exemplary quality. Subsequently, we've expurgated dead links, redirects, and malicious data.

We have developed an advanced web toolkit for annotators, utilizing Chrome[1], designed for the manual acquisition of three types of data modalities. To mitigate legal risks and ensure data privacy compliance, our selection process is confined to publicly accessible web pages without access restrictions. Subsequent to data collection, each screenshot undergoes rigorous examination by two experienced data scientists, a measure implemented to guarantee the quality of the web page data. This includes anonymizing data wherever feasible and considering the ethical implications of our data collection and publication methods.

2.3 Data Annotation

We've meticulously orchestrated a protocol to ensure the pinnacle of data quality:

Standard Unification In an endeavor to mitigate discrepancies arising from varied annotator interpretations, we've formulated and promulgated a comprehensive benchmark accompanied by guidelines for annotators. For each stipulated standard, illustrative exemplars, both exemplary and deficient, are presented to vividly elucidate the normative expectations.

Annotator Training and Selection We solicited annotation contractors from the public, selecting 21 annotators to be trained by experienced data scientists. After two-week training, we invited annotators to participate in multiple rounds of trial annotation, which were then reviewed by data ex-

[1] https://www.google.com/intl/en-US/chrome/dev/, under BSD 3-Clause License

Scoring Dimension	Evaluation Criteria
Relevance	**Excellent**: Closely aligns with the topic and provides valuable extensions beyond **Ordinary**: Generally in line with the topic or slightly off-topic **Bad**: Deviates from the topic severely
Professionalism	**Excellent**: Includes in-depth content or a high degree of professionalism **Ordinary**: Contains article of normal quality with no obvious writing issues **Bad**: Contains obvious defects in the article or invaluable content
Design	**Excellent**: Includes exquisite and user-friendly web page layout **Ordinary**: Normal layout design that can obtain useful information easily **Bad**: Contains chaos design that hinders user's information acquisition
Authenticity	**Ordinary**: Contains no deceptive content such as cropping and stitching **Bad**: Contains deceptive content attracting clicks to acquire illicit profits
Overall Score	**Excellent**: Includes no specific defects and excels in more than one dimension **Ordinary**: Includes no specific defects or contains slight defects **Bad**: Contains severe defects that damage user experience

Table 1: An Overview of the Four Key Sub-Dimensions and Overall Scoring Methodology. This framework assesses web pages based on topical relevance, content professionalism, design, and authenticity.

perts. After examination, we chose the top 10 highest accuracy annotators for this dataset.

Multi-dimension Annotation Annotators were tasked with scoring individual dimensions of the web page initially. Having aggregated these dimension-specific ratings, an overall score was conferred, contingent upon the collated ratings. To enhance elucidation, we mandated the provision of annotation elucidatory notes corresponding to each data entry.

Batch Verification Given the extensive magnitude of the dataset, it was methodically segmented for processing. Adhering to a phased enhancement strategy, initial batch sizes encompassed 3k, 6k, 10k, and 20k web pages, subsequently augmenting to 30k for successive batches. Each segment constituted 10,000 units of data; After annotation, a random assortment of 30% of the dataset underwent contractor scrutiny, while a 1% subset was meticulously examined by data scientists.

Cross-annotation Verification To avoid missed and incorrect annotations, an inter-annotator validation mechanism was implemented. Three annotators critically appraised the labeled web content, registering a commendable congruence rate of 91.2%. Any emergent discrepancies were subject to expert adjudication, ensuring resolution and conformity.

2.4 Dataset Rebalancing

To counteract the detrimental impact of long-tail datasets on model performance, as noted by Zhang and Luo (2019), we executed data rebalancing on 310,000 annotated web page datasets. This intervention addressed the imbalance in data distribution, particularly between data points rated as bad and excellent. The revised data distribution is presented in Table 2.

3 Dataset Analysis

3.1 Data Format

As illustrated in Figure 2, our dataset's input compartmentalizes into three distinct segments: a visual screenshot of the web page, the textual content, and the corresponding HTML+CSS file. The central textual corpus embodies the pivotal content of the page, exemplified by encyclopedic articles in encyclopedia websites and the question-answer pairs of QA. To maintain layout fidelity, we integrate essential CSS files into the core HTML structure using <style> tags, simultaneously preserving JavaScript files. Graphical screenshots are obtained using a browser interacting with specific URLs, processed via a rendering engine. Annotators for each web domain expanded full texts, removed ads, and captured visuals covering four screen lengths.

3.2 Dataset Statistics

This section describes the statistics and characteristics of ***WebQuality*** from various perspectives.

The Statistics Distribution of Dataset Table 2 shows the overall distribution of ***WebQuality*** datasets, which contains a total of 65,442 samples, each labeled by score from 4 sub-dimensions. The

Scoring	Bad	Ord.	Exc.	Sum
Relevance	8098	46961	10383	65442
Professionalism	4112	39096	22234	65442
Design	10772	48782	5888	65442
Authenticity	3847	61595	None	65442
Overall Score	15553	27043	22846	65442

Table 2: The statistical distribution of the dataset regarding dimensions and scores, where 'Ord.' represents ordinary and 'Exc.' represents excellent.

distribution of scores in the Overall Score dimension is relatively balanced, while the distribution in other dimensions is relatively unbalanced, especially for the auth dimension, which has only two bins and the number of normal doc samples is 20 times greater than the number of non-authoritative docs. This is mainly because the vast majority of real-world web pages are normal, but the distribution of high-quality web pages and low-quality web pages is relatively scattered and has the characteristics of many types, which also brings challenges to quality task evaluation and modeling.

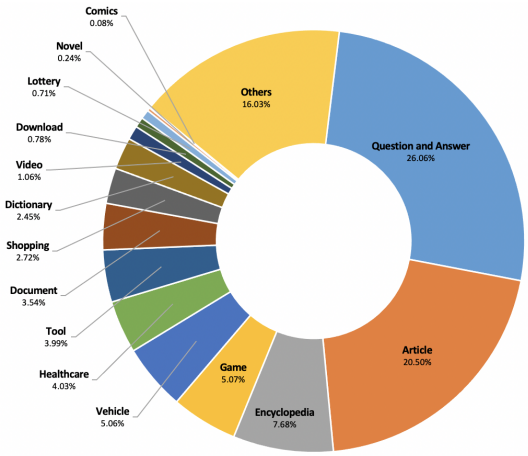


Figure 3: Distribution of Web Page Types

Distribution of Web Page Types Figure 3 shows the distribution of web page types in ***WebQuality*** dataset. Under the premise of ensuring a balanced label distribution, we try to select web page types according to the distribution of real web page types. For example, the question and answer page is mainly displayed in the form of Question-Answer, of which the question and answer page and article page account for 46%, which matches the real distribution in search engines. Cheng et al. (2023) demonstrated the effectiveness of web page

Figure 4: Distribution of Domains in Web Pages

evaluation by modeling web page types, and we believe that counting the distribution of web page types is equally important for web page quality assessment.

Distribution of Domains in Web Pages The web pages in the dataset can be categorized into 26 domains, including 16 main domains with more than 1000 samples. Figure 4 lists the distribution of instances belonging to different topics. Apart from the top 16 domains, how to model and understand different quality issues under different topics can be a matter of ongoing concern.

3.3 Dataset Comparison

As shown in Table 3, we compared our dataset with various datasets in similar fields, including web ranking, web question-and-answer and quality scoring datasets. DuReader (Wu et al., 2020) is a widely used, automatically generated web page ranking dataset. This dataset mainly focuses on the article sorting task. Although it surpasses ours in scale, it lacks the rigor of manual labeling. CoQAN (Wang et al., 2020) is the closest to our dataset in terms of our domain. It compares which of two news docs has better quality instead of directly annotating and scoring. It outputs quality scores through pairwise comparisons, but it lacks modal information, and its data volume is only half of ours. Datasets such as ASAP (Prize, 2019), ASAP++ (Mathias et al., 2018) and ACEA (He et al., 2022) predominantly concentrate on the critical evaluation of articles, including the logic, language and other dimensions of college entrance examination essays. The WebSRC dataset (Chen et al., 2021), in its structural composition, bears the closest resemblance to ours. It also provides HTML, screenshot, and text, but its

Dataset	Task	Lang.	Html	Img.	Text	Ann.	Dims.	Doc.
DuReader	Ranking	CN	✗	✗	✔	✗	✗	8.9M
WebSRC	QA	EN	✔	✔	✔	✔	✗	6.4K
ASAP	AES	EN	✗	✗	✔	✔	✔	21K
ASAP++	AES	EN	✗	✗	✔	✔	✔	12K
ACEA	AES	CN	✗	✗	✔	✔	✔	1.2K
CoQAN	Quality	CN	✗	✗	✔	✔	✗	38K
WebQuality(Ours)	Quality	CN	✔	✔	✔	✔	✔	65K

Table 3: Comparison of Datasets Across Various Tasks. 'Ann.' denotes whether the dataset has been manually annotated, while 'Dims.' indicates if the dataset encompasses multiple scoring dimensions.

primary focus lies in QA tasks, and its size is only 1/10 of ours. In general, the ***WebQuality*** dataset is oriented to Chinese web page quality assessment, and it provides a variety of inputs and large annotations, which can provide the community with high-quality datasets.

4 Method

4.1 Text Embedding

Text is the main carrier of web page content, and text modeling is crucial for web page quality assessment. We take BERT (Devlin et al., 2019) as the text encoder, which is widely adopted in numerous NLP tasks.

$$\vec{h}^{(bert)} = BERT(x) \tag{2}$$

4.2 ScreenShot Embedding

In order to obtain the visual information in the web page screenshot, we process the web page screenshot through a series of image operations. We use ViT (Dosovitskiy et al., 2020) as image encoder.

$$\vec{h}^{(vit)} = VIT(i) \tag{3}$$

4.3 HTML Process and Embedding

Influenced by the methodology proposed in (Cheng et al., 2023), our study utilizes the Graph Attention Network (GAT) delineated by (Veličković et al., 2018) for HTML modeling. This approach interprets HTML elements as nodes within a graph framework. We define node features via discretization and bucketing, modeling these based on key CSS styles, as detailed in Table 4.

Classification	Feature Name
Location	height,width,position type
Content	font size,font style, line height,font weight
Layout	border,padding,margin,visibility, display style,outline style,outline width

Table 4: Selected CSS style contents for GAT's node feature.

Graph construction To formulate layout information for various categories of web pages, we construct the graph structure required for GAT through the parent-child node relationship of the DOM tree.

Feature Pre-processing We design a series of features for each node type, to capture the layout information of the web page. More specifically, for continuous features (e.g., height, line height and margin), a non-uniform interval division strategy is employed to divide the continuous interval into several buckets, which can ensure that there are enough training samples in a single bucket.

GAT Model Function In particular, the architecture of GAT is composed by stacking multiple graph attention layers, each of which can be defined as

$$\vec{h}^{(k+1)} = \sigma\left(\sum_{m \in \mathcal{N}_n} \alpha_{nm} \mathbf{W}_1^{(k)} \vec{h}_m^{(k)}\right) \tag{4}$$

$$\vec{h}^{(gat)} = h_{html}^{l} \tag{5}$$

where $\sigma(.)$ is an activation function and α_{nm} is the attention value between node n and node m. Here, $\vec{h}_m^{(k)}$ represents the embedding of node m in the k-th layer. The attention value is learned

Method	Rel.	Pro.	Des.	Auth.	**Avg-sub**	**OS**
	F1	F1	F1	F1	Avg-F1	F1/Acc
BERT	56.55	58.11	40.08	51.44	51.55	63.76/66.01
ViT	47.62	47.33	40.35	49.46	46.19	50.40/53.41
GAT	46.34	45.54	35.73	**52.03**	44.91	50.34/52.59
GPT4 ZeroShot	25.85	27.17	17.85	32.13	25.75	31.08/43.50
GPT4 OneShot	28.41	29.31	20.34	32.09	27.54	34.01/46.55
Hydra	**58.13**	**60.48**	**41.55**	51.47	**52.91**	**66.68/68.41**
-w/o text	49.55	52.34	41.31	49.23	48.11	54.61/57.57
-w/o screenshot	57.60	59.54	40.63	51.00	52.19	65.46/67.26
-w/o HTML+CSS	57.87	59.89	40.90	50.57	52.31	65.68/67.49

Table 5: Experimental Results and Ablation Study Outcomes. The abbreviations 'Rel.', 'Pro.', 'Des.', 'Auth.', and 'OS' denote the sub-dimensions of Relevance, Professionalism, Design, Authenticity, and Overall Score, respectively. 'Avg-sub' refers to the average F1 score across these four sub-dimensions. The Overall Score incorporates the F1 score and accuracy for various models.

to selectively propagate information from node n to node m. We use last layer l's hidden state of <html> node as representation of the HTML.

4.4 Feature Integration

Multi Subnetwork Comprehension For the sake of simplicity, we adopt the strategy of freezing the three encoder modules, and then concatenate the outputs of the three encoders, and then pass through two fully connected layers to obtain the final web page classification s.

$$\vec{h} = concat(\vec{h}^{(bert)}, \vec{h}^{(vit)}, \vec{h}^{(gat)}) \tag{6}$$

$$\mathrm{s} = argmax(softmax(linear(\vec{h}))) \tag{7}$$

Where $concat$ indicates the concatenation of the hidden representations of the three modalities. Equation 7 represents the concatenated hidden representations passing through a fully connected layer, with the final scoring results obtained via the softmax and argmax functions. Experiment details can be seen in appendix A.1.

5 Experiments

5.1 Evaluation Metrics

For the Overall Score dimension, we use macro-F1 score (F1) and accuracy (Acc) as the evaluation indicators of the effect, which measures the overlap of the predicted score and the ground truth. For sub-dimensions, macro-F1 score is used for evaluation.

5.2 Comparative Analysis of Baseline Models

In this study, we benchmark our method against several robust baseline models, each detailed subsequently:

BERT: Recognized for its excellence in supervised text understanding, we employ a variant of BERT tailored for Chinese, considering it a potent benchmark in text analysis.

ViT: Serving as a prototypical visual encoder, ViT, pre-trained on imagery, has demonstrated proficiency across various visual tasks.

GAT: Chosen for its efficacy in structured data interpretation, we utilize the original GAT configuration with a two-layer structure, aiming to analyze the HTML structure of web pages.

GPT4 ZeroShot: GPT4 (OpenAI, 2023), known as a leading large language model (LLM), is employed in its zeroshot variant to assess its capability in evaluating web page quality.

GPT4 OneShot: Recognizing GPT4's strong in-context learning abilities, we explore its upper limits in web page evaluation using a oneshot approach, with the prompt detailed in A.3.

5.3 Experiment Results

Overall Performance Table 5 presents the comprehensive experimental outcomes on the ***WebQuality*** dataset. Notably, the ***Hydra*** outperformed others in the Overall Score dimension, leading in both F1 score and accuracy. ViT and GAT registered F1 score of 50.40% and 50.34%, which indicates the importance of structure in web page quality assessment. BERT-alone closely mirrored Hydra's

effectiveness, underscoring the BERT encoder's robustness and highlighting the pivotal role of core textual content in web page quality assessment. The LLM's poor performance in this task indirectly reflects the challenge of the quality assessment task. Overall, ***Hydra***, BERT, ViT, and GAT have advanced in the Overall Score dimension, but there is still room for further improvement, reflecting the complex nature of web page quality evaluation and the need for robust metrics and models.

Ablation Study Our examination revealed that the exclusion of any single modality from models adversely affects their performance. Specifically, the omission of text data incurred the most significant reduction in F1 score, registering a 12.07% decrease. This was succeeded by a 1.22% decrease due to the lack of screenshot data, and a 1% decrease when HTML+CSS data was absent.

5.4 Discussions and Limitations

5.4.1 The Answer to Previous Questions

Empirical evidence obtained from our experimental investigations provides insightful answers to the two pivotal queries postulated in Section 1.

Our Dataset's Efficacy in Assessing Web Page Quality Table 5 demonstrates that models proficient in certain sub-dimensions attain superior overall score, while those limited to a single modality frequently exhibit deficiencies in alternate sub-dimensions. This finding highlights the integral relationship between sub-dimensional scores and the overall score of our dataset, enhancing the model's capacity for multi-faceted analysis. Our dataset, targeting a spectrum of quality evaluation criteria, combine supplementary multi-modal data to augment web page quality assessment. However, four scoring sub-dimensions of our dataset may not be suitable for all circumstances, depending on new focal points of specific quality discernment tasks. The potential for exploring further sub-quality dimensions remains an area for future investigative endeavors.

Our Dataset and Model's Efficacy in Web Page Modeling from Each Modality Our research implements a multi-modal joint model to elucidate the interrelationships and correlative impacts among diverse modalities. We executed a series of ablation studies by systematically excluding three-modal data within the ***Hydra*** framework. As evidenced in Section 5.3, the omission of any modality's data invariably results in a detrimental effect on our model's performance, manifesting as reductions in evaluation metrics. Consequently, it is imperative to utilize a comprehensive dataset encompassing all modalities to achieve optimal results in web page modeling. The indispensable nature of data from the triad of modalities—human visual (screenshot), rendering (HTML+CSS), and semantic perspectives—is corroborated in our findings. This tri-modal approach, to our current understanding, presents a notably holistic methodology for web page analysis. The necessity for integration of additional modalities remains an open question, warranting further empirical investigation.

5.4.2 Is LLM the Answer to Web Quality Assessment?

In our empirical investigation, we conducted a rigorous evaluation of the most recent iteration of the Generative Pre-trained Transformer model, GPT-4, using our specialized task dataset. Despite its demonstrable proficiency across a spectrum of other tasks, the performance metrics observed with our dataset indicated suboptimal outcomes. This highlights the limitation of relying solely on GPT-4's text-based capabilities to effectively capture the complexities inherent in our specific task. Moreover, the challenge of integrating capabilities for interpreting visual data such as screenshot and HTML+CSS structures into GPT's framework remains an unresolved area of inquiry in this domain.

6 Conclusion

In this study, we introduce ***WebQuality***, a comprehensive Chinese multi-modal dataset specifically designed for evaluating web page quality, which comprises HTML+CSS, text, and visual screenshot. Our objective centers on a holistic assessment of web pages, scrutinizing four specific sub-dimensions. Evaluations with various baseline models on this dataset underscore the intricacies of assessing web page quality. We propose the ***Hydra*** model, a novel contribution that utilizes HTML+CSS, text, and screenshot data for cohesive analysis. Despite setting a new benchmark, its limitations in certain aspects highlight the need for further exploration in effective multi-modal integration. This research contributes to advancing methodologies in web page quality assessment, with future directions aimed at developing versatile models for enhanced practical applications of web page data such as web data filtering for LLM's pre-training.

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A Appendix

A.1 Implementation Details

We have detailed the implementation specifics for three modalities.

Text Processing and Embedding: Leveraging the bert-base-uncased model from Hugging Face [2], our approach adheres to BERT's text input limitations by selecting the initial 512 tokens of content. A dedicated BERT-only model is independently trained for this purpose. Within the ***Hydra*** model framework, we keep the BERT module's parameters static, and the [CLS] token from the final layer serves as the quintessential representation for text encoding.

Screenshot Processing and Embedding: To establish uniformity in the dimensions of web page screenshots, we adopted a standardized agent size of 400x900 for screenshots acquired manually. In order to align with the Vision Transformer (ViT)'s pre-training specifications, operations like Resize and RandomResizedCrop were implemented. We utilized the ViT-B/16 model as the encoder[3], with its parameters initially pre-trained on the ImageNet-21K dataset for an image resolution of 224x224, specifically employing the 21k_224_224 parameter configuration[4]. Subsequent to the fine-tuning process, we froze the parameters of the ViT model, selecting the encoding output from the [CLS] token of the network's final layer as the ViT module's output.

[2] https://huggingface.co/bert-base-uncased

[3] https://github.com/google-research/vision_transformer

[4] https://huggingface.co/google/vit-base-patch16-224-in21k

Model Name	ZeroShot	OneShot
GPT-4	**31.08**	**34.01**
GPT-3.5	30.39	29.71

Table 6: Performance on Different LLMs

HTML Processing and Embedding: We utilize Beautiful Soup [5] for parsing web page source codes, thereby extracting their hierarchical structures. Employing Depth First Search (DFS), we extract adjacency relationships from the DOM tree, recording the nodes and their parent-child edge connections within the DOM structure recursively. For GAT training, We randomly initialize the weights of the GAT, and train it on our dataset for 10 epochs with a learning rate of 0.01. After the training process, freeze network parameters for prediction during model fusion.

A.2 Large Language Model Comparison

This section offers a detailed comparative evaluation of various Large Language Models (LLMs) across diverse configurations, focusing on their aggregate performance metrics. Table 6 clearly indicates GPT-4's ascendancy over GPT-3.5, reflecting its more robust task comprehension capabilities. Notably, the task in question involves multi-modal inputs, which suggests that relying solely on GPT's text-based variant may not be the most effective approach. This highlights the imperative for incorporating sophisticated multi-modal features to maximize the efficacy of these language models in diverse application scenarios.

A.3 GPT Prompt

In the ensuing section delineated as Section 5, we enumerate the prompts utilized for the **GPT4 oneshot** and **GPT4 zeroshot** paradigms. Comprehensive details pertaining to these prompts are methodically presented in Table 7. We proffer the Web page quality assessment criteria, designated as <quality_criteria>, pertinent to our dataset, thereby elucidating the task at hand. Subsequent to this exposition, the Language Model (LLM) is furnished with the title (<web_title>) and the web content (<web_content>) of each web page. Specifically, for the **GPT4 OneShot** configuration, an exemplar web page (<incontext_example>) is additionally provided.

[5] https://www.crummy.com/software/BeautifulSoup/bs4/doc/, under MIT License.

Template	Setting
Please classify the quality of the web page according to the following title, content, and web page quality assessment criteria, and output: good, average, or poor; Web page Quality Assessment Criteria: <quality_criteria>; Title: <web_title>; Content: <web_content>.	**ZeroShot**
Please classify the quality of the web page according to the following title, content, and web page quality assessment criteria, and output: good, average, or poor; Web Page Quality Assessment Criteria: <quality_criteria>; Title: <web_title>; Content: <web_content>; Example: <incontext_example>.	**OneShot**

Table 7: Prompt Display: The content enclosed in angle brackets represents the placeholder of a template.

A.4 Dataset Details

In this section, a lucid exemplification of our dataset is presented. Owing to the extensive length of the CSS code, only a fragment thereof is exhibited. The specific segment of the data under consideration is delineated in Table 8. In our methodology, the JavaScript code is retained within the original HTML file, accompanied by the provision of the corresponding CSS style file for each HTML document. Subsequently, the primary textual content of a singular web page is furnished. Post the process of web rendering, a screenshot corresponding to each discrete data entry is meticulously archived.

A.5 Acknowledgement

We employed anonymous accounts for website access and made concerted efforts to remove sensitive data. Nevertheless, due to the intrinsic characteristics of web pages, potential privacy-related risks may persist. Simultaneously, the dataset presented in this study is exclusively intended for academic research and will not be utilized for any other purposes. All pertinent legal regulations and licenses have been meticulously examined to guarantee compliance.

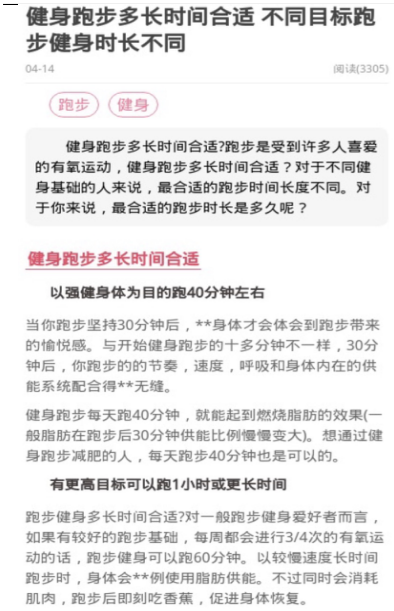
Content	Data Modality
<html>... 健身跑步多长时间合适 以强健身体为目的跑40分钟左右 当你跑步坚持30分钟后，**身体才会体会到跑步带来的愉悦感。与开始健身跑步的十多分钟不一样，30分钟后，你跑步的的节奏，速度，呼吸和身体内在的供能系统配合得**无缝。 健身跑步每天跑40分钟，就能起到燃烧脂肪的效果(一般脂肪在跑步后30分钟供能比例慢慢变大)。想通过健身跑步减肥的人，每天跑步40分钟也是可以的。 有更高目标可以跑1小时或更长时间 跑步健身多长时间合适?对一般跑步健身爱好者而言，如果有较好的跑步基础，每周都会进行3/4次的有氧运动的话，跑步健身可以跑60分钟。以较慢速度长时间跑步时，身体会**例使用脂肪供能。不过同时会消耗肌肉，跑步后即刻吃香蕉，促进身体恢复。 ...</html>	**Html**
.ad_hongren img{ width: 100%; } ::before, ::after { –tw-content: ”; } html, :host { line-height: 1.5; -webkit-text-size-adjust: 100-moz-tab-size: 4; tab-size: 4; } ...	**Css**
健身跑步多长时间合适 以强健身体为目的跑40分钟左右 当你跑步坚持30分钟后，**身体才会体会到跑步带来的愉悦感。与开始健身跑步的十多分钟不一样，30分钟后，你跑步的的节奏，速度，呼吸和身体内在的供能系统配合得**无缝。健身跑步每天跑40分钟，就能起到燃烧脂肪的效果(一般脂肪在跑步后30分钟供能比例慢慢变大)。想通过健身跑步减肥的人，每天跑步40分钟也是可以的。有更高目标可以跑1小时或更长时间 跑步健身多长时间合适?对一般跑步健身爱好者而言，如果有较好的跑步基础，每周都会进行3/4次的有氧运动的话，跑步健身可以跑60分钟。以较慢速度长时间跑步时，身体会**例使用脂肪供能。不过同时会消耗肌肉，跑步后即刻吃香蕉，促进身体恢复。	**Text**
	**ScreenShot**
一般最适宜健身多久,健身跑步多长时间合适?	**Title**
内容完整，轻微采集	**Annotation Remark**
OverallScore: 0; Relevance: 1; Professionalism: 1; Design: 1; Authenticity: 0	**Score**

Table 8: Detailed Examples of Multimodal Data of Our Dataset