

WebSRC: A Dataset for Web-Based Structural Reading Comprehension

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Abstract

Web search is an essential way for human to obtain information, but it's still a great challenge for machines to understand the contents of web pages. In this paper, we introduce the task of web-based structural reading comprehension. Given a web page and a question about it, the task is to find an answer from the web page. This task requires a system not only to understand the semantics of texts but also the structure of the web page. Moreover, we proposed WebSRC, a novel **Web**-based **Structural Reading Comprehension** dataset. WebSRC consists of 0.44M question-answer pairs, which are collected from 6.5K web pages with corresponding HTML source code, screenshots, and metadata. Each question in WebSRC requires a certain structural understanding of a web page to answer, and the answer is either a text span on the web page or yes/no. We evaluate various strong baselines on our dataset to show the difficulty of our task. We also investigate the usefulness of structural information and visual features. Our dataset and task are publicly available at <https://speechlab-sjtu.github.io/WebSRC/>.

1 Introduction

Web pages are the most common source of human knowledge and daily information. With the help of modern search engines, people can easily locate web pages and find information by simply typing some keywords. However, traditional search engines only retrieve web pages related to the query and highlight the possible answers (Chen, 2018), they can't understand the web pages and answer the query based on the contents. The rapid development of question answering systems and knowledge graph enables search engines to answer simple questions directly (Chakraborty et al., 2019),

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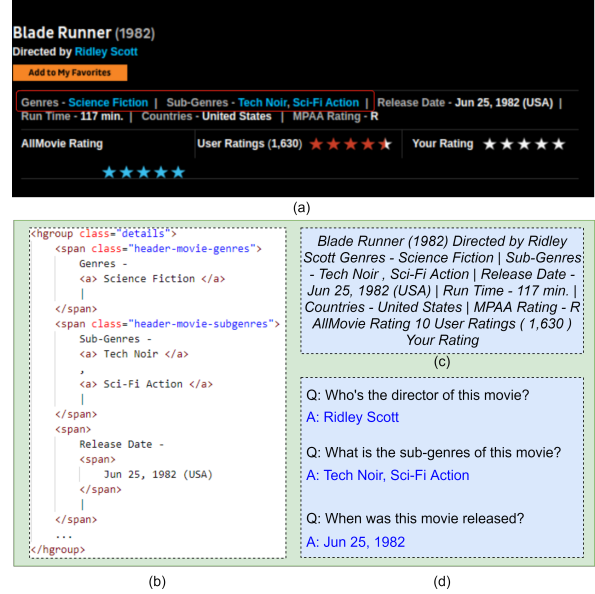


Figure 1: Examples for web page, HTML and the corresponding DOM tree. (a) is the origin web page. (b) is the HTML code for the content in the red box. Each HTML tag begins with a starting tag and ends with a closing tag (with a slash in tag). `<hgroup>` stands for a horizontal group, `` stands for a content span and `<a>` is used for a hyperlink. (c) contains some sample questions for the web page.

but they still fail to perform question answering on arbitrary given web pages. The difficulty lies in the variety of web pages and the complexity of the web layouts, which requires a system not only to consider the textual contents but also the structures of web pages.

There are two kinds of structures for each web page: *spatial* structure and *logical* structure. The spatial structure is how the information visually organized, and the logical structure is how the information organized by semantics. Figure 1(a) shows an example. The image shows the spatial structure of the web page, e.g. how the texts are arranged and what's their relative position. The logical structure can be deduced by the spatial struc-

ture and the semantics of the texts. For example, this image introduces the information about a movie with the title at the top, followed by a detailed description and ends with the rating of the movie. A human can easily answer the questions in Figure 1(d) by referring to the relevant section in the logical structure. But for computers, it’s hard to understand the logical structure by just taking the spatial structure (the image) as input for the lack of common sense. Computers need to infer the answers by the font size, the color and the spatial relations between texts, let alone they need to extract texts from the image and understand them. What if only utilize the plain text from the web page to answer the questions? Figure 1(c) shows the texts extracted from the web page. As we can see, the layout structure is lost in the plain text, and the text is just a concatenation of short phrases without a meaningful context. It would be difficult to answer questions only based on such texts.

An alternative way for computers to understand web pages is to parse the HTML (Hypertext Markup Language) document, i.e. the source code of the web page. It describes the structure of web pages, and use *HTML elements (tags)* to display the contents. Figure 1(c) shows the HTML code corresponding to the part of the web page highlighted in the red box. HTML is a kind of semi-structured document (Buneman, 1997), where tags with different meanings serve as separators, thus the content wrapped by each tag can be seen as different semantic parts. It’s also called the “self-describing” structure. An HTML document can be parsed into a tree-like structure called DOM¹ (Document Object Model), where the tree nodes are elements in the HTML, and texts are all leaf nodes in the tree. An HTML DOM tree can serve as a structural representation of the web page, where visually similar items on the web page would be sub-trees with similar structures. Due to the complexity of rendering HTML code into a web page, a single HTML would be not enough to represent the whole web page. We can partially infer the logical structure from the HTML tags and their contents, and take the DOM tree as a weak spatial structure, but how machines can leverage HTML to answer questions remains a challenge.

To promote researches in question answering on web pages, we introduce WebSRC, a dataset for reading comprehension on structural web pages.

The task is to answer questions about web pages, which requires a system to have a comprehensive understanding of the spatial structure and logical structure. WebSRC consists of 6.5K web pages and 0.44M question-answer pairs about web pages. For each web page, we manually chose one segment from it and saved the corresponding HTML code, screenshot, and metadata like positions and sizes. Questions in WebSRC were created for each segment. Answers are either text spans from web pages or yes/no. Taking the HTML code, screenshot, metadata as well as the question as input, a model is to predict the answer from the web page.

To summarize, our contributions are the following:

- We proposed the task of web-based reading comprehension, which is a multi-modal machine reading comprehension task that focuses on understanding web pages.
- We created a large dataset for web-based reading comprehension consisting of 0.44M QAs and 6.5K web page segments, where HTML code and additional visual features are also provided.
- We evaluated several baselines on WebSRC and showed the difficulty of our task.

2 Related Work

There are four research areas related to our task: machine reading comprehension, information extraction, layout analysis, and visual question answering.

Machine reading comprehension (MRC) models have achieved excellent performance on plain text corpus (Zeng et al., 2020) in recent years. Traditional datasets for machine reading comprehension (Talmor et al., 2018; Yang et al., 2018; Rajpurkar et al., 2016, 2018; Choi et al., 2018; Reddy et al., 2019; Lai et al., 2017) contain plain text passages and QAs about them. To answer the questions, machines should understand the textual context. However, HTML code is different from the ordinary textual corpus in the form of semi-structured documents, and texts extracted from HTML are just short phrases without context, which is an obstacle for the traditional MRC model to understand. Recently, multi-modal MRC has gained the interest of researchers. Multi-modal MRC datasets with both images and texts

¹https://en.wikipedia.org/wiki/Document_Object_Model

are proposed, such as MovieQA (Tapaswi et al., 2016), TQA (Kembhavi et al., 2017), COMICS (Iyyer et al., 2017) and RecipeQA (Yagcioglu et al., 2018). The question types in these datasets include natural language or cloze, and the answer could be natural language or multi-choice. Images in these datasets provide different information from texts, and texts are supplementary descriptions for images. For example, TQA includes texts and diagrams from science courses of middle school. Readers need to read the passage and diagram simultaneously to gain a comprehensive understanding. However, HTML and screenshots of web pages are different representations for the same content. The image can be regarded as the rendered result of HTML, while HTML can be considered as an abstract representation for the image.

Information extraction for web pages has been investigated intensively (Chang et al., 2006). Previous studies of extracting information from web pages mainly focus on building templates for HTML DOM tree, called wrapper Induction (Kushmerick, 2000; Flesca et al., 2004; Kushmerick et al., 1997; Muslea et al., 1999), or using well designed visual features like font sizes, element sizes, and positions (Zhu et al., 2005, 2006). These methods require abundant human labor to label templates and analyze features, which makes it hard to generalize to unseen websites. Bronzi et al. (2013) proposed a dataset called WEIR, consisting of 40 websites from 4 domains. Hao et al. (2011) proposed SWDE, which contains 124,291 web pages from 80 websites, and Lockard et al. (2019) expanded SWDE for openIE. All these datasets only contain HTML code for extraction, and the task is to extract pre-defined attributes of entities in web pages, e.g. the author of a book. There are two main drawbacks of this task. First, this task ignores the abundant information carried by the rendered web pages. Secondly, the terms to be extracted need to be defined beforehand, which lacks the flexibility of generalizing to new terms or new domains.

Layout analysis (Binmakhshen and Mahmoud, 2019) is the task to analyze document images like contracts, bills, and business emails. The task focuses on a series of topics like document classification, information extraction from scanned documents, and layout recognition. For instance, IIT-CDIP (Lewis et al., 2006) and RVL-

CDIP (Harley et al., 2015) are collected for document classification. Jaume et al. (2019) proposed FUNSD for form understanding and Huang et al. (2019) organized SROIE competition for receipt understanding. PubLayNet (Zhong et al., 2019) and DocBank (Li et al., 2020) are proposed to benchmark the task of layout recognition in academic papers. Comparing to web pages, documents in these datasets are relatively simpler and more structured, while web pages are much more complex in organizing information. The terms to be analyzed (e.g. the name and price of a product) are relatively stable in layout analysis, while web pages may contain various information terms that hard to be pre-defined. Besides, document images lack the structural description like HTML, which is available on web pages and is vital to understand the layout of web pages.

The task of **VQA** (visual question answering) (Antol et al., 2015) is to answer questions about an image. Questions in VQA would be about the objects in the image, such as the number or the color of the objects. The most relevant topic is text VQA (Mishra et al., 2019; Singh et al., 2019; Mathew et al., 2020), where questions in this task are about the texts in the image. For example, given an image about a book, the question can be “What’s the title of the book?”. There is no existing text or layout description available in the image, and the images from the real-world introduce additional challenges to understand the content. However, the texts from web pages are well organized and easy to be recognized. The main difficulty of reading comprehension for web pages is to understand the spatial relations between texts.

3 Data Collection

3.1 Task Definition

The task of machine reading comprehension for web pages can be described as: given the context \mathcal{C} and a question q , predict the answer a . In our task, the context can be HTML code, screenshots, and the corresponding metadata. Our task can be formulated as:

$$\mathcal{F}(\mathcal{C}, q) = a \quad (1)$$

where $\mathcal{F}(\cdot)$ is the machine reading comprehension model.

The construction of our dataset consists of three stages: web page collecting, web page cleaning,

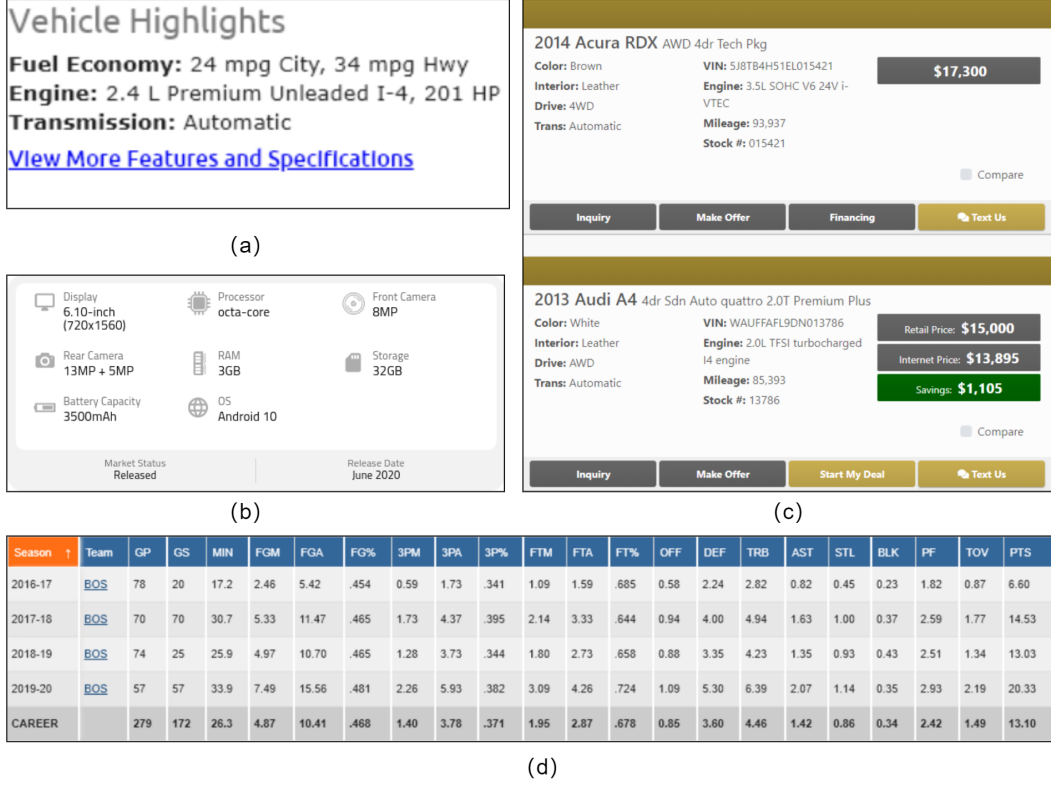


Figure 2: Examples for three types of web pages. (a) and (b) are web pages of type *KV*, (c) is a web page of type *comparison*, (d) is a web page of type *table*.

question labeling, and data augmentation. We will describe each stage in detail below.

3.2 Web pages collecting

In this stage, we collect web pages from different domains. When crawling the web pages, we didn't save the whole page but only chose some segments, because a complete web page may contain ads or additional structure like navigation tabs, which bring too much noise into the web page and make the task much harder. For each segment, we save the corresponding HTML code, the screenshot of the segment, and additional metadata (including the location and the size of each HTML element, the color of texts, and the CSS *font* attribute of each text). We used Selenium² to collect all the data. According to the different ways of displaying information, we category web pages into three types: *KV*, *comparison*, and *table*. We use different crawling strategies for different types of web pages, as described below.

KV Information in this type of web page is presented in the form of “*key: value*”, where the *key* is an attribute name and the *value* is the corre-

sponding value. See Figure 2(a) and Figure 2(b) for illustration. This kind of web pages can be found from the detail page of an entity, e.g. a car or a book. We manually choose the section that describes attributes about the entity from the web page and crawl it.

Comparison This type is similar to type *KV* but with a major difference: web pages of type *comparison* contain several entities with the same attributes. For instance, in Figure 2(c), there are two cars in the image and they form a comparison. A comparison web page can be divided into several *KV* web pages and it's usually organized as a long list. When crawling a comparison web page, we didn't crawl the whole entity list but only select a segment containing two or three entities, which keeps the size of saved data within a reasonable range.

Table Web pages of type *table* use a table to present information. A table contains the comparison between rows naturally but unlike the type *comparison*, it uses a unified header to represent attributes and each row in the table only contains values. Note that the form of tables may vary from website to website. Figure 2(d) shows information about three cars. We only select the table area

²<https://www.seleniumhq.org/>

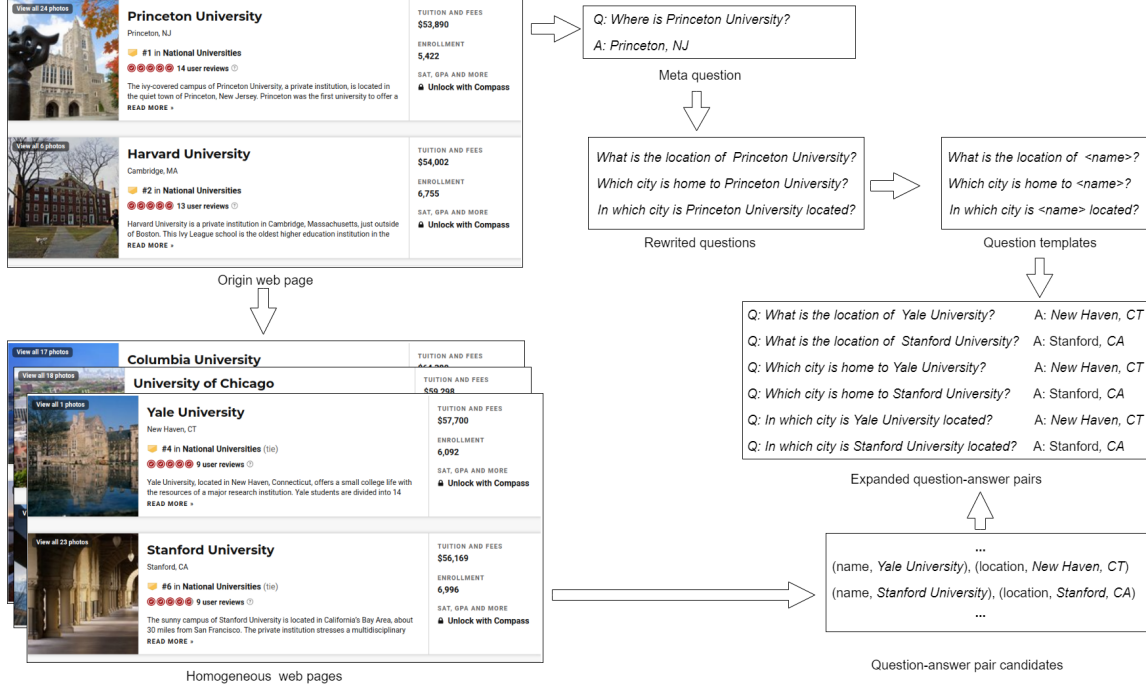


Figure 3: The pipeline for augmenting data.

on the web page for crawling, and we also slice sub-tables by rows from the whole table when the original table is too large.

In this phase, we collected 70 websites from 11 domains, resulting in 6577 web pages in total.

3.3 Web pages cleaning

We removed all non-ascii characters, extra line breaks, and space in HTML documents. Tags that have little influence on web page structure are removed, including `<script>` and `<style>`. Properties of HTML tags are also removed except for `<class>`, `<id>`, `<title>` and `<aria-label>`, for these properties only serve as descriptions of a tag. We add an additional attribute called *tid* to all tags, which will be used in the labeling stage.

3.4 Question Labeling

We recruited in-house annotators to label questions and answers. We showed screenshots to annotators and asked them to create questions about the content on the image. All questions should be answerable by the screenshot, and the answer should be a text shown in the image or yes/no. For websites of type KV, we required annotators to focus on attributes (e.g. the price of a car, the author of a book) and ask questions about them. Web pages of type comparison and type table contain more than one entity, so we asked annotators to

create questions about the attributes of one specific entity. We also collect questions with constraints, for example “What’s the price of the brown car?” has a constraint of “brown”.

We only asked annotators to create one simple question for each attribute and we regarded these questions as meta-questions. Most of the meta-questions are in the form of “What’s the *<attr>* of the *<ent>*?”, where *<attr>* stands for the specific *attribute* and *<ent>* stands for the entity in the web page. These questions lacked the diversity of expressions. To solve this problem, we published a question rewriting task on AMT (Amazon Mechanical Turk) to polish meta-questions. Workers on AMT were shown a screenshot and a meta-question with the answer, and their task is to rewrite the given question without changing the meaning. We encouraged the worker to use more complex expressions and use synonyms for attributes if possible. For each meta-question, we collected on average 5 questions.

3.5 Data Augmentation

In this phase, we expanded the polished questions to all web pages. Although the structure of different websites varies a lot, web pages under the same website have a similar structure. In order to automatically apply collected questions to all homogeneous web pages, we processed the data as

follows:

Abstract questions into templates. For each question, we replaced the specific values with placeholders. For example, “What’s the price of the book *Harry Potter*?” would become “What’s the price of the book *<book-name>*?”.

Find key-value pairs. For each website, we manually analyzed the structure and located all attributes and the corresponding values. We extract all key-value pairs (e.g. (*genre*, *Science Fiction*), (*release-date*, *Jun 25, 1982*)) from all web pages, which would serve as question generation candidates.

Generating questions. For each web page, we looped over all question templates and all question generation candidates, replaced the placeholders with *key* and replaced the origin answer with *value*, resulting in a great number of question-answer pairs. To balance the amount of data from different websites, we randomly sampled the generated question-answer pairs to form the final dataset.

After data augmentation, we obtained 442226 question-answer pairs in total. The whole process of data augmentation is illustrated in Figure 3.

4 Dataset Analysis

In this section, we conduct throughout analysis of the numerical characteristic of WebSRC.

4.1 Dataset statistics

Type	#website	#webpage	#QA
KV	34	3214	177633
Comparison	15	1339	84189
Table	21	1901	180404

Table 1: Statistics of different type of websites.

The distribution of different website types in various domains is shown in Figure 4. As the figure illustrated, not all domains contain three website types while type KV almost exists in all domains. Websites of type comparison are concentrated in the domain of goods, i.e. *auto*, *book*, in the form of item comparison. Most web pages with type table belong to the domain *sports*, which contain the score data of players.

The statistics of different types of websites are shown in Table 1. The most common type of website is type KV, which accounts for about a half. The least type of website is type comparison with

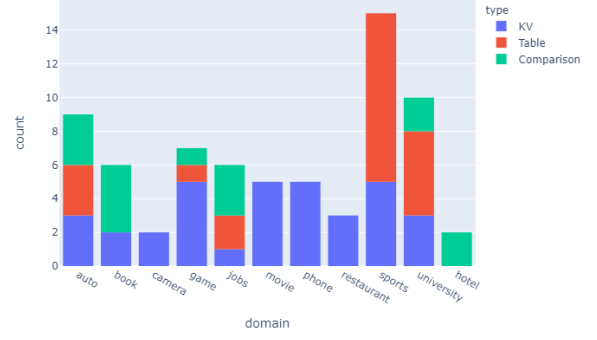


Figure 4: Distribution of different type of websites in different domains.

only 20% of the total websites. For we can generate a question for each value in a table, the proportion of question-answer pairs of type table is much bigger than its number of websites, which is about 40%.

Figure 6 shows the data distribution in different domains. Domains *auto*, *university* and *sports* account for half of the data, and *hotel*, *camera* and *restaurant* are the domains that with least data. This distribution can attribute to the amount of information carried by websites and the amount of information in different domains that is interested by people.

4.2 Questions in WebSRC

WebSRC consists of two kinds of questions: wh-questions and yes-no questions. We analyze the frequency of the leading trigram of two question types respectively. Questions starting with “what” are the most common questions, and questions starting with “what is the” account for 26.5% of the whole dataset. We visualize the distribution of the trigram prefix of “wh-” questions without the prefix “what is the” in Figure 5(a). We also found imperative sentences (“*Tell me the...*”) in our dataset, which is created by the crowdsource workers. The trigram prefix distribution of yes-no questions is shown in Figure 5(b). As shown in the figure, words like *Is*, *Can* and *Does* are strong indicators of yes-no questions. The length of the question is sensitive to the specific item name on the web page, i.e. book name. The average length of questions is 8.37.

4.3 Answers in WebSRC

Answers in WebSRC are relatively short, 86.38% of which are within 3 words and 55.47% answers

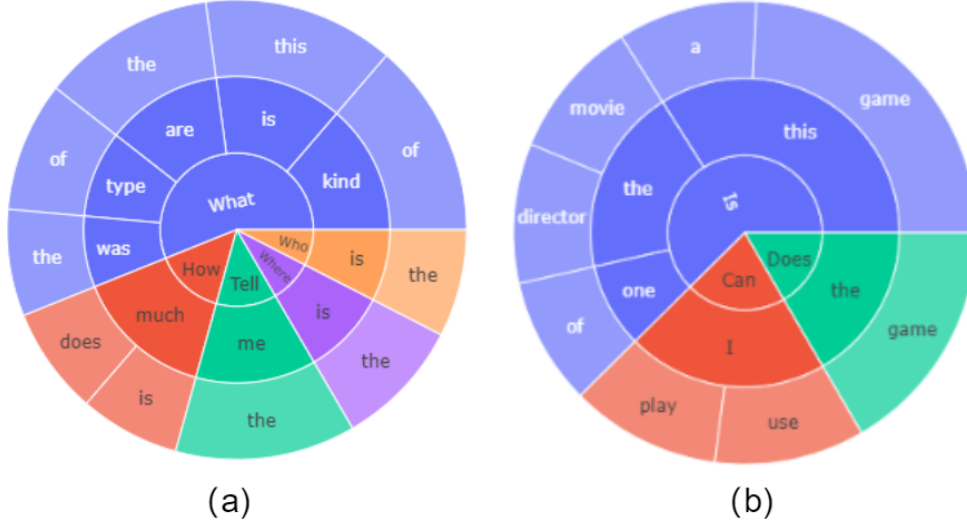


Figure 5: The distribution of 10 most frequent trigram prefixes of questions. Figure (a) is the distribution for wh-questions without the prefix “what is the”. Figure (b) is the distribution for yes-no questions.

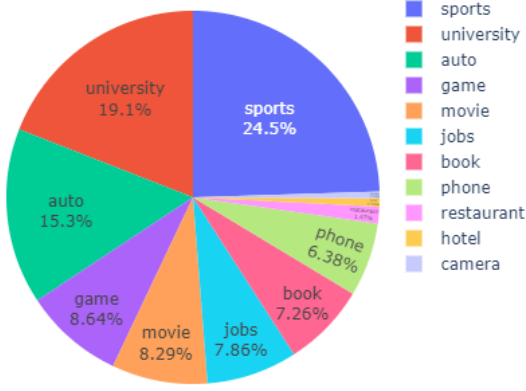


Figure 6: Data distribution in different domains.

have only one word. All answers are extracted from the HTML code except for yes-no questions. However, a text that is visually a whole may be scattered in multiple HTML tags. The example shown in Figure 1 illustrates this phenomenon. The line “Sub-Genres - Tech Noir, Sci-Fi Action” is separated by “<a>” tags. Besides, even though an answer could be fully contained by a tag, the tag may contain additional texts and the answer would be a span of the text from this tag. For example, the answer to the third question in Figure 1 is a sub-span of whole tag text *Jun 25, 1982 (USA)*. To precisely locate the answers, we first define **the text of an HTML node**: the text of an HTML node is the concatenation of its descendant text nodes, where the order of text nodes is produced by deep-first search, see Algorithm 1 for detail. With this definition, an answer can be represented by the HTML node that fully contains it

Algorithm 1: The algorithm for obtaining a node of an HTML tag.

Function GetNodeText (*node*) :

Input: An HTML node

Output: The text of the HTML node

if *node* is a text node **then**

return *node*;

else

 text = [];

for *n* in *node.childNodes* **do**

 text.append(GetNodeText (*n*))

return Concat(text)

and the starting position in the text of the HTML node. Only 2.71% answers are distributed in multiple tags and 13.44% answers are sub-spans of the text of HTML nodes.

4.4 HTML statistics

We explored the distribution of HTML tags in WebSRC. Figure 7 shows the relative proportion of top 10 frequent HTML tags and top 10 frequent HTML tags containing an answer. Three most common tags are <div>, and <td> on all pages, which are also most frequent tags containing answers. <div> and are used for separating an area, while <td> represents a table cell. This observation indicates that the type of tag may imply the semantics of the content. Though <div> is the most frequent tag, <td> is much more likely to contain an answer, for the reason that <div> is

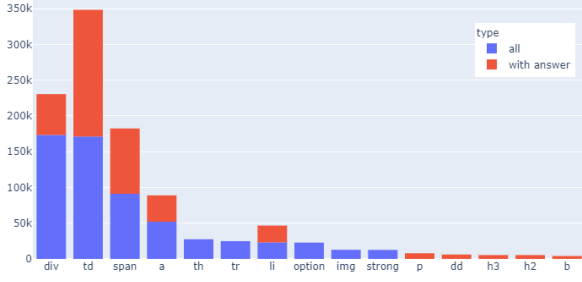


Figure 7: Distribution of HTML tags. (a) is the top 10 HTML tags in all HTML code. (b) is the top 10 HTML tags containing an answer.

often used in framing the web page while `<td>` is commonly used for presenting a value. The average number of HTML elements in web pages is 171. The mean depth of HTML DOM trees is 9.8 and the mean depth of tags containing answers is 7.1, which means the upper nodes would provide more structural information and the lower nodes would contain more specific information.

5 Baseline Models

We propose three baseline models for WebSRC. They take different kinds of context into consideration. We describe these models in detail below.

5.1 Pre-trained Language Model with Text (T-PLM)

In the first baseline, we convert the HTML code into non-structural pure text, and simply utilize Pre-trained Language Model (PLM), e.g. BERT (Devlin et al., 2018), to predict answer spans. We call this model T-PLM.

We first go over the HTML code and delete all the HTML tags, retaining all plain texts. We also add two additional word *yes* and *no* for yes-no question prediction. Here the context \mathcal{C} in Eq. (1) is the resulting plain text. We tokenize the resulting plain text and the corresponding question, then concatenate them to form the input sequence \mathbf{x} . Then the start and end probabilities of an answer span can be obtained as follows:

$$\mathbf{Z} = \text{PLM}(\mathbf{x}),$$

$$\mathbf{p}^s, \mathbf{p}^e \propto \text{SoftMax}(\text{Linear}(\mathbf{Z})),$$

where \mathbf{Z} is the resulting sequence representation calculated by PLM; \mathbf{p}^s and \mathbf{p}^e are probability distributions for each token to be the start token and then end token of the answer span, respectively; $\text{Softmax}(\cdot)$ and $\text{Linear}(\cdot)$ are the softmax layer

and feed-forward linear layer. The objective function in the training stage is the cross-entropy loss of the start and end probabilities:

$$\mathcal{L} = -\frac{1}{N} \sum_i^N [\log(p_{y_i^s}^s) + \log(p_{y_i^e}^e)],$$

where N is the number of training examples. y_i^s and y_i^e are the start position and the end position of question answer of i -th example, respectively. Accordingly, $p_{y_i^s}^s$ and $p_{y_i^e}^e$ are the y_i^s -th and y_i^e -th element in \mathbf{p}^s and \mathbf{p}^e , respectively. In addition, after obtaining the predicted answer spans, we go over the HTML code again to find the smallest tag which contains the whole answer, and take it as the predicted answer tag.

5.2 Pre-trained Language Model with HTML (H-PLM)

In HTML code, structural information is contained in HTML tags. We try to leverage tag information in our second baseline. We call this baseline H-PLM.

We first go over the HTML code and delete all attributes of each HTML tag. The resulting HTML tags only contains the angle brackets, tag names, and the possible slashes (the remaining strings look like `<div>`, ``, `</p>`, etc). We view these “clean” HTML tags as special tokens and add them to the input sequence. For example, the HTML code in Figure 1 is processed as “` Fuel Economy ...`”. For each kind of HTML tag, we initialize its embedding randomly and learn it during training. We regard these sequences with HTML tags as the context \mathcal{C} in Eq. (1) here. The model architecture of H-PLM is similar to T-PLM except for the input.

5.3 Visual Information Enhanced Pre-trained Language Model (V-PLM)

As introduced in Section 1, only HTML is not enough to represent the whole web structure due to the web page rendering. In the third baseline, we take the visually rich information from web pages into consideration. We call this model V-PLM. It consists of three parts: PLM, visual information enhanced self-attention block, and classification layer.

As shown in Figure 8, we first concatenate the question and the corresponding HTML code as a sequence, then feed it into a pre-trained language model to obtain the representation of each token in

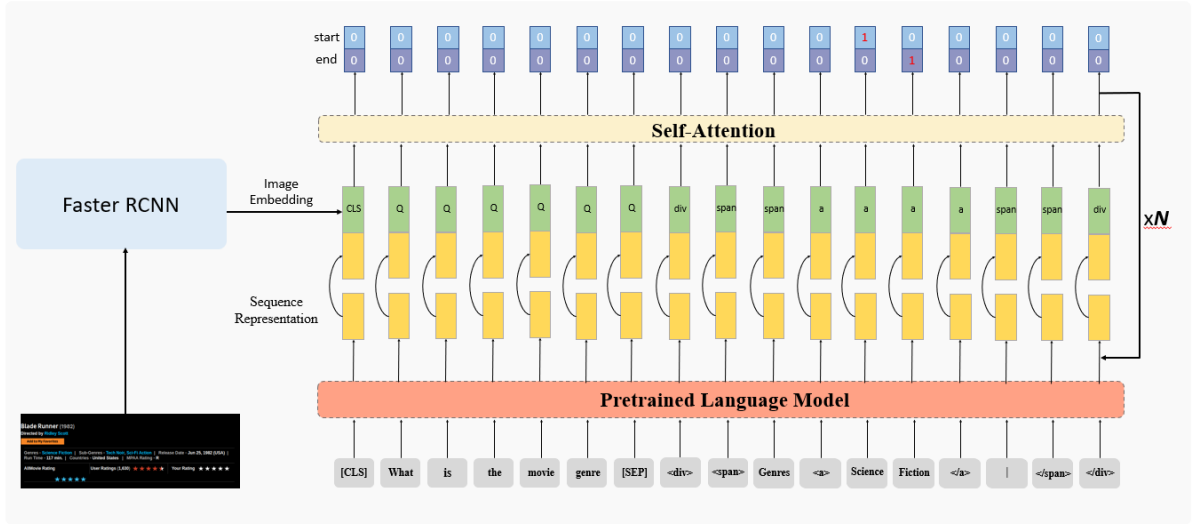


Figure 8: The model architecture of V-PLM.

the sequence. In order to utilize the visual structure of the web page, each token representation is concatenated with a visual embedding from the corresponding screenshot. As described in Section 3.3, for each tag in HTML, we have saved its bounding box in the screenshot. With the bounding box, we can obtain the visual embedding for each tag in the screenshot using the toolkit Faster R-CNN (Ren et al., 2016). For each text token in HTML, its visual embedding is the same as that of its parent tag in the DOM tree, e.g. in Figure 8, the visual embeddings of `<a>`, *Science*, *Fiction*, `` are all the same. For [CLS] and each token in the original question, their visual embeddings are zero vectors.

The visual feature enhanced representation is then fed into a self-attention block, which is repeated N times. The final representation is then sent to the classification layer to produce the starting and ending probability, which is the same as T-PLM and H-PLM.

6 Experiments

6.1 Dataset Splits

We manually divide our dataset into train/dev/test set at the website level, where the training set contains 50 websites, dev and test contain 10 websites respectively. Both the dev set and the test set have all three types of websites and have a similar distribution of website types. The detailed statistics of each set are shown in Table 2.

Split	#website	#webpage	#QA
Train	50	4549	307315
Dev	10	906	73507
Test	10	994	81838

Table 2: Statistics of dataset splits.

6.2 Evaluate Metric

We use three kinds of metrics to evaluate our task.

Exact match This metric is used to evaluate whether a predicted answer is completely the same as the ground truth. It will be challenging for those answers that are only part of the tag text.

F1 score This metric measures the overlap of the predicted answer and the ground truth. We split the answer string into tokens and compute F1 score on them.

Path overlap score When the model predicts an answer from a wrong tag but the text of the answer is identical to the ground truth, exact match and F1 score may fail. Therefore we introduce path overlap score, a tag level metric that evaluates the accuracy in structure. An HTML document is a DOM tree, so for every tag, there exists a unique path from the root `<HTML>` element to the tag. We compute the path overlap score between path p_1 and p_2 as following:

$$\text{POS} = \frac{|P_1 \cap P_2|}{|P_1 \cup P_2|},$$

where POS stands for path overlap score, P_1 and P_2 are the sets of elements in the path p_1 and p_2 respectively. The $|\cdot|$ denotes the size of a set.

Models	w/ text	w/ tag	w/ screenshot	DEV			TEST		
				EM	F1	POS	EM	F1	POS
T-PLM (BERT)	✓			51.42	61.07	77.39	44.08	51.95	71.49
H-PLM (BERT)	✓	✓		59.84	64.56	78.52	52.71	58.24	75.00
V-PLM (BERT)	✓	✓	✓	61.19	65.72	80.71	55.95	61.38	76.90
T-PLM (ELECTRA)	✓			62.48	70.19	83.43	57.16	66.17	76.66
H-PLM (ELECTRA)	✓	✓		68.45	71.98	84.36	64.39	68.36	81.79
V-PLM (ELECTRA)	✓	✓	✓	70.19	72.78	85.59	66.96	73.00	83.27

Table 3: Experimental results of various baselines on dev and test sets. EM stands for exact match score, and POS stands for path overlap score.

6.3 Experiment Setup

We train our baselines on the training set and select the best models on the dev set based on the exact match score. We use uncased BERT-Base and ELECTRA-Large as our backbone PLM models. The learning rate is $1e-5$. The batch size is 32. We use Adam optimizer with a linear scheduler. For V-PLM, the number of self-attention block is 3.

6.4 Results & Error Analysis

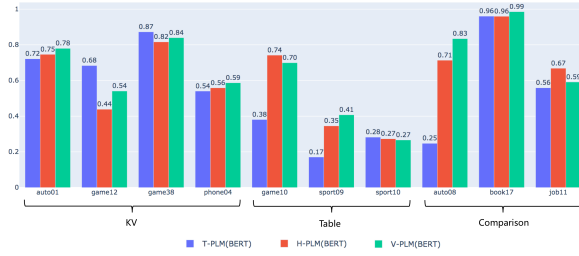


Figure 9: The performance (EM score) comparison of three baselines on 10 different websites on dev set. These websites fall into three categories: *KV*, *Table*, and *Comparison*.

The experimental results on the dev set and the test set are shown in Table 3. We can find that no matter which pre-trained language model (PLM) is used, more context information (i.e. text, HTML tag, screenshot) used, the performance is better. Specifically, comparing H-PLM with T-PLM, we find that H-PLM outperforms T-PLM with a large margin. In T-PLM, only texts in HTML is used, while in H-PLM, both texts and tags are used. These tags can implicitly model the visual structure of web pages to some degree. Comparing V-PLM with H-PLM, we find that V-PLM can outperform H-PLM, which indicates explicit visual features can provide additional structural information. However, we can also find that the improvement of performance is not very large. This is because the Faster-RCNN toolkit used here

is pre-trained on nature images. It may not well apply to screenshots of web pages. In the future, there is a lot of room for exploration of how to make good use of visual information.

From Table 3, we can also find that ELECTRA-based models consistently outperform BERT-based models. ELECTRA is among the best models on text-based MRC tasks, e.g. SQuAD2.0 (Rajpurkar et al., 2018). However, ELECTRA can achieve about 90 EM score on SQuAD2.0, while it can only achieve about 70 EM score on WebSRC. It indicates that WebSRC is still challenging for the best pre-trained language models.

In Figure 9, we further compare the performance of three baseline models on different websites. We find that on three websites, i.e. *game10*, *sport09*, and *auto08*, H-PLM and V-PLM outperform T-PLM with a large margin. Both of *game10* and *sport09* fall into the category of *table*, and *auto08* fall into the category of *comparison*. Generally, for *table* and *comparison* web pages, it is required that models have good understanding of global structure of web pages. From Figure 9, we can also find that among three types of web pages, these models perform worst on *table* web pages.

7 Conclusion

In this paper, we introduce WebSRC, a multi-modal machine reading comprehension dataset for web-based reading comprehension. The task is to answer questions about given web pages. We evaluate several baselines on our dataset, and the experimental result showed that incorporating layout features and textual contents is crucial to web understanding, but how to utilize such structural information requires further investigation. We hope this work can push the research on web reading comprehension forward, and encourage the community to develop efficient techniques for web understanding.

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