The Klarna Product Page Dataset: Web Element Nomination with Graph Neural Networks and Large Language Models

Alexandra Hotti *alexandrahotti@gmail.com*
KTH Royal Institute of Technology, School of EECS
Klarna

Riccardo S. Risuleo *riccardosven@gmail.com*
Klarna

Stefan Magureanu *smagureanu@gmail.com*
Klarna

Aref Moradi *rfmrd619@gmail.com*
Klarna

Jens Lagergren *jens.lagergren@scilifelab.se*
KTH Royal Institute of Technology, School of EECS
SciLifeLab

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Abstract

Web automation holds the potential to revolutionize how users interact with the digital world, offering unparalleled assistance and simplifying tasks via sophisticated computational methods. Central to this evolution is the web element nomination task, which entails identifying unique elements on webpages. Unfortunately, the development of algorithmic designs for web automation is hampered by the scarcity of comprehensive and realistic datasets that reflect the complexity faced by real-world applications on the Web. To address this, we introduce the Klarna Product Page Dataset, a comprehensive and diverse collection of webpages that surpasses existing datasets in richness and variety. The dataset features 51,701 manually labeled product pages from 8,175 e-commerce websites across eight geographic regions, accompanied by a dataset of rendered page screenshots. To initiate research on the Klarna Product Page Dataset, we empirically benchmark a range of Graph Neural Networks (GNNs) on the web element nomination task. We make three important contributions. First, we found that a simple Convolutional GNN (GCN) outperforms complex state-of-the-art nomination methods, and further enhance its performance using a Reversible GNN (RevGNN) architecture. Second, we introduce a training refinement procedure that involves identifying a small number of relevant elements from each page using the aforementioned GNN. These elements are then passed to a Large Language Model for the final nomination. This procedure significantly improves the nomination accuracy by 10.9 percentage points on our challenging dataset, without any need for fine-tuning. Finally, in response to another prevalent challenge in this field – the abundance of training methodologies suitable for element nomination – we introduce the *Challenge Nomination Training Procedure*, a training method that further boosts nomination accuracy.

1 Introduction

In the rapidly advancing field of web automation (Yao et al., 2022; Lin et al., 2020; Wang et al., 2022; Deng et al., 2023), an overarching goal is to provide users with seamless assistance when completing mundane tasks online. By harnessing the full potential of web automation, users will no longer be forced to manually navigate through tedious workflows. Instead, intrusive pop-ups will be preemptively closed, and forms will be automatically completed, regardless of the specific website being accessed. Automation features like these could significantly enhance the user experience in, for example, super-apps equipped with integrated browsers that require advanced automation capabilities. Apart from saving users' time and attention, web automation paves the way for creating personal online assistants. These assistants could, for example, allow a user to purchase a specific pair of shoes at the best possible price with just a simple instruction.

One factor driving the recent heightened interest in web automation is the rise of Large Language Models (LLMs). The impressive performance demonstrated by LLMs, combined with the fact that models such as GPT-4 (OpenAI et al., 2023) have been trained on HTML data, has catalyzed a surge in research focused on using LLMs as, for instance, foundation models for navigation on webpage datasets (Furuta et al., 2023; Zhao et al., 2023; Deng et al., 2023; Zheng et al., 2024; Wang et al., 2023; Kim et al., 2023; Zheng et al., 2023; Gur et al., 2023).

Beyond navigation capabilities, many web automation features also require the ability to precisely locate information on a page. For instance, when purchasing the aforementioned shoes for a user, it is necessary to extract and compare prices from product detail pages across a large number of vendors. Additionally, as Deng et al. (2023) highlight, automation capabilities could be integrated as plugins for models like ChatGPT, enabling on the fly retrieval of information from HTML websites based on user inputs, instead of relying on predefined APIs for each web service. Clearly, many web automation features require a combination of navigation and information retrieval capabilities. However, as far as we are aware, few, if any, studies or datasets comprehensively address both aspects.

The scarcity of publicly accessible, large-scale, and realistic webpage datasets is a significant barrier to progress in this field. Previous research has been limited to simplified, simulated webpages (Gur et al., 2023; Yao et al., 2023; Shi et al., 2017a), or confined to pages from a narrow selection of websites (Hao, 2011; Yao et al., 2023). Such datasets fail to reflect the complexities faced by real applications on the Web, which consists of tens of millions of websites, each with thousands of elements and layout patterns that vary significantly across different sites. This shortage may stem from the fact that collecting and annotating a comprehensive web page dataset is a costly and time-consuming undertaking, requiring skills more commonly found among web developers than machine learning researchers.

As a significant contribution to the community, we introduce the *Klarna Product Page Dataset*[1]. Figure 10 presents screenshots of four rendered pages from our dataset. The Klarna Product Page Dataset is designed to emulate a scenario encountered by, for instance, an autonomous shopping assistant. This assistant is tasked with navigating through product pages across a multitude of different websites to extract product information. The goal could be to identify a specific item requested by a user at a given price point, then add this item to the cart and proceed to the checkout page. However, note that in the empirical evaluation carried out in this work, we solely focus on identifying the elements individually.

Furthermore, the Klarna Product Page Dataset dataset comprises over $50,000$ real e-commerce pages from $8,175$ websites, with five manually labeled action and information elements per page (See Figure 2). To the best of our knowledge, this positions our dataset as the largest available labeled webpage dataset in terms of the number of websites. Additionally, while the majority of public datasets primarily consist of English pages, a unique advantage of Klarna Product Page Dataset is its inclusion of pages from eight distinct geographic markets. This inclusion enables the capability to assess generalizability across multiple languages (See Table 1). Finally, recent studies have also leveraged webpage screenshots to explore computer vision research for the web (Zheng et al., 2024; Kumar et al., 2022). To support future similar efforts, we have developed a complementary dataset that includes screenshots of the rendered pages from our dataset.

As a starting point for research on the *Klarna Product Page Dataset*, we benchmark the performance of various neural networks on *Web element nomination*, which is a fundamental concept for automating tasks on the web. We define Web element nomination as the process of identifying a unique element from a specific class on a webpage. One of the challenges that makes this task particularly demanding is that among potentially

[1]Available at github.com/klarna/product-page-dataset under the CC BY-NC-SA license.

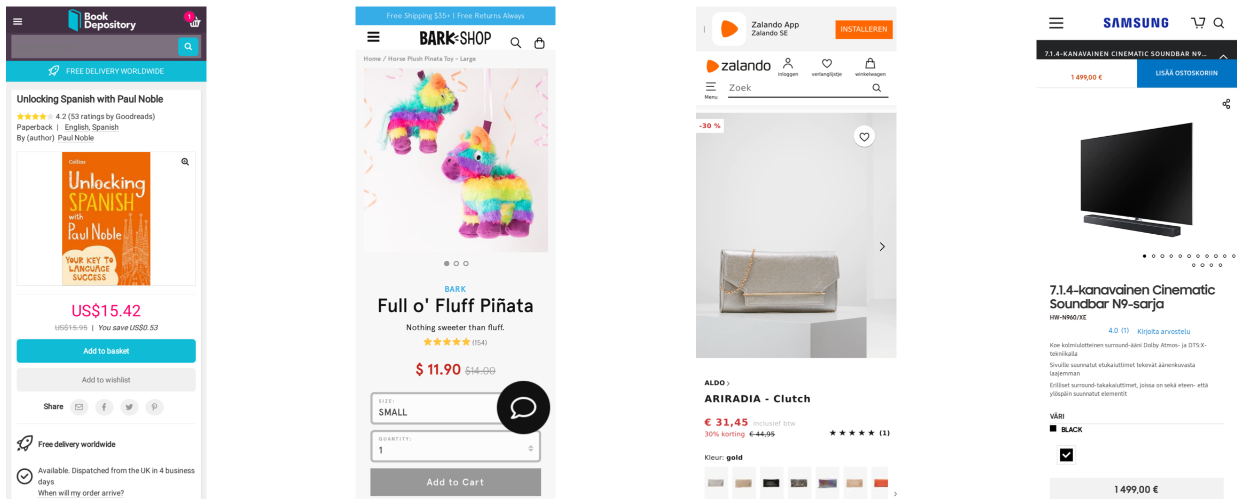


Figure 1: Four pages from the Finnish, Dutch and US markets in our dataset.

thousands of nodes on a page, only one element belongs to each class. For this purpose, we train several neural networks on the Document Object Model (DOM) tree representations of webpages, using three popular families of graph neural networks (GNNs): recurrent GNNs (Tree Long Short-Term Memory networks), convolutional GNNs (GCNs), and attention-based GNNs. Our aim is to compare their performance in web element nomination and identify the most promising GNN family for future research on the *Klarna Product Page Dataset*. We also compare their performance against state-of-the-art (SOTA) methods FreeDOM (Lin et al., 2020) and DOM-Q-NET (Jia et al., 2019), both of which are fairly intricate algorithms. FreeDOM, for instance, requires a two-stage training process, and both algorithms utilize information from the entire DOM tree to represent a single element. We discovered that a surprisingly simple GCN, which solely uses information from local neighbourhoods around each node in the DOM tree, outperforms these SOTA methods. We further enhance the GCN by incorporating it into a Reversible GNN (RevGNN) architecture (Li et al., 2021). RevGNN improves both memory and parameter efficiency through reversible connections, group convolutions, and weight tying, enabling us to scale up to 20 layers and further boost the final nomination accuracy. These finding highlights the potential of employing GCNs as building blocks in more advanced web element nomination architectures in future research.

We subsequently investigate three methodologies aimed at further enhancing the web element nomination performance. Firstly, we explore whether the text present on the page is informative for nominating web elements. Specifically, we use a pre-trained *language model* to create embeddings of the text on the page, which we then add to the set of features. Our findings indicate that models incorporating text in general achieve higher average accuracy. Surprisingly, for certain tasks, the included text proves to be non-informative and, in fact, reduces performance. Secondly, applying LLMs to the entire HTML of realistic pages is unfeasible, partly due to limited context windows but mainly due to the high costs associated with processing a large number of tokens. To address this, we explore an approach where we significantly enhance the performance of the highest-performing GNN model with a post-training refinement step where an LLM is applied to a small subset of the highest ranked elements of each page. Finally, we address the absence of a standardized training methodology for element nomination[2]. To this end, we propose and evaluate a novel training approach that considerably improves nomination accuracy.

To summarize, our aim is to lower the entry barriers in this exciting field through the following contributions:

1. We introduce the *Klarna Product Page Dataset*[3], which consists of 51,701 manually labeled product pages from 8,175 e-commerce websites. The dataset is suitable for tasks such as element nomination,

[2]For comparison, see vertex nomination, as in Fishkind et al. (2015); Coppersmith (2014) This field typically involves very small numbers of graphs (in this context, webpages), rendering these methods unsuitable here.

[3]Available at https://github.com/klarna/product-page-dataset under the CC BY-NC-SA license.

and evaluation or fine-tuning of LLMs. We have also created a complementary dataset with the corresponding screenshots of the webpages for future CV applications.

2. We adapt and apply six algorithms from three of the most popular families of GNNs to a web element nomination task, namely recurrent GNNs (Tree Long Short-Term Memory networks), convolutional GNNs (GCNs) and attention based GNNs. We also investigate the performance of SOTA baselines for element nomination. In particular, we identify that *GCN-Mean*, a simple 2-layer GCN, outperforms the *second-best* model by an impressive margin of 9.2 percentage points measured in average nomination accuracy. We then enhance the scalability of this algorithm by employing RevGNN, which uses the GCN as a base model.

3. We explore a post-training nomination refinement step using an LLM. Specifically, we use a trained RevGNN algorithm to filter out all elements except the top ten for each class on every webpage in the test set. We then use GPT-4 to perform the final nomination based on the local HTML content of these filtered elements. Our results show that this refinement step substantially enhances nomination accuracy across all explored tasks, resulting in an average increase of 10.9 percentage points.

4. In element nomination, one would commonly train a model to classify elements and then evaluate the model based on its nomination performance. We refer to this approach as the *Basic Nomination Training Procedure*. To steer the classification objective towards the nomination objective, we introduce the novel *Challenge Nomination Training Procedure* (CNTP). Our results demonstrate that CNTP substantially improves nomination accuracy by approximately 5 percentage points for our best model.

5. We assess the impact that the text on the pages has on nomination accuracy by utilizing a *language model* to embed the text and integrate it as a feature. Our findings demonstrate that this considerably improves performance in specific nomination tasks, such as when identifying the Buy Button.

2 The Klarna Product Page Dataset

We collected the Klarna Product Page Dataset dataset over several months between 2018 and 2019. The dataset comprises $51,701$ product pages from $8,175$ distinct e-commerce merchants. It is conveniently divided into 80% training and 20% test sets, which ensures that pages from the same website do not appear in both the training and test sets. Table 1 presents an overview of the dataset statistics. Each page in our dataset is saved as an MHTML file, which includes all images and assets required to render the page. Furthermore, every page in the dataset has 5 labeled elements: 2 corresponding to action elements (*buy button* and *cart button*) and 3 to information elements (*product price*, *product name*, and *product image*). These labels have been manually annotated by human analysts. In our experiments, we also consider a 6th, more abstract label: the *subject node*, defined as the lowest common ancestor of all other labels. An example page screenshot

Table 1: An overview of the Klarna Product Page Dataset.

market	language	# sites	# pages	median # nodes
DE	German	2,941	16,765	1,391
US	English	1,794	11,003	1,394
GB	English	1,360	11,144	1,291
FI	Finnish	1,125	5,623	779
AT	German	899	1,316	1,499
SE	Swedish	619	4,866	1,450
NO	Norwegian	180	852	1,477
NL	Dutch	130	132	1,628
Total		8,175	51,701	1,308

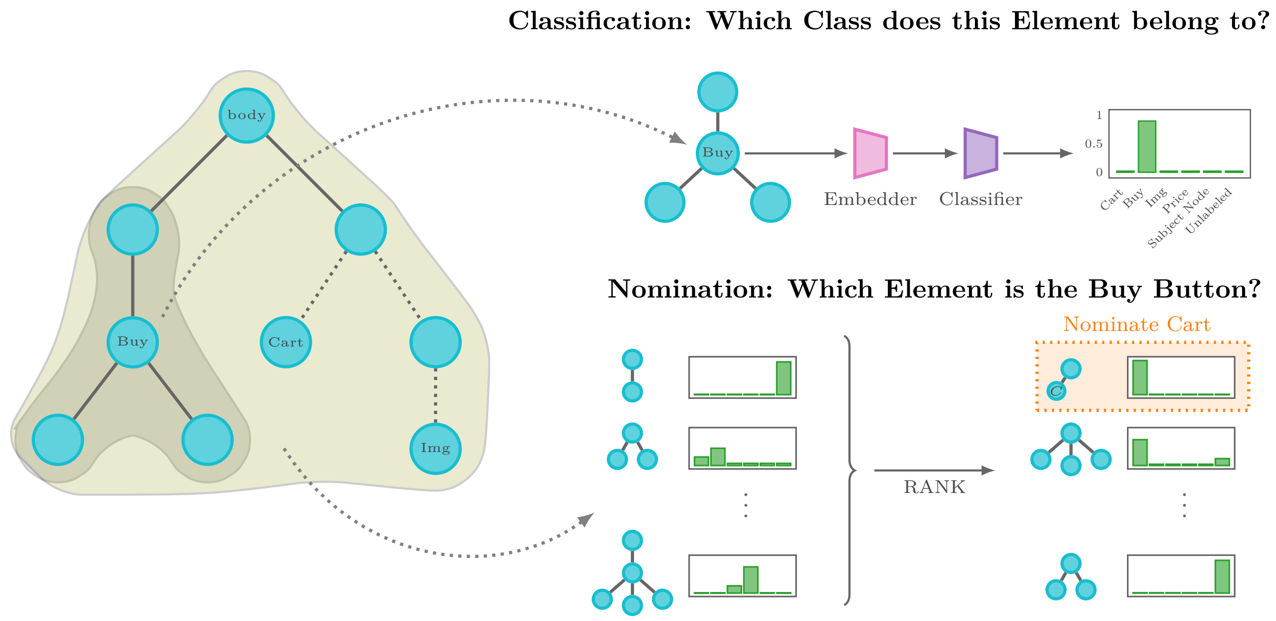

Classification: Which Class does this Element belong to?
body
Buy
Cart
Img
Buy
Embedder
Classifier
1
0.5
0
Cart
Buy
Img
Price
Subject Node
Unlabeled
Nomination: Which Element is the Buy Button?
Nominate Cart
RANK

Figure 3: **Difference between nomination and classification:** A DOM-tree representation of a webpage is depicted to the left. During the classification process, the GNN embedder takes a node and its context, here being its directly neighboring nodes, as input. The output from the embedder is then fed into a classification layer that produces classification scores. In element nomination, the model is applied to every node in the tree. For each label type, the resulting classification scores are ranked across all nodes, and the node receiving the highest rank is nominated for that specific label type. For example, here we see how the node receiving the highest ranking for the *Cart Button* label is nominated as the *Cart Button* element of the page.

from our dataset with marked labels is shown in Figure 2. Additionally, for convenience, we have created a complementary dataset of page screenshots, suitable for computer vision research.

3 Element nomination

Precisely identifying the correct element before executing any action in web automation is vital. In automation features, element nomination plays a crucial role as it solves the common subtask of identifying a single element on a webpage for a specific action. Since we often have only one opportunity to perform a task, incorrect actions, such as clicking the wrong button or filling in the wrong form, can degrade the user experience.

Unfortunately, there is no established training objective specifically for web element nomination (For further details on the complexities of formulating an objective for element nomination, see Appendix A.6) instead, the common practice is to train a model to classify elements and then assess its nomination performance. The distinction between classification and nomination is illustrated in Figure 3. During training, a GNN embeds a small subset of nodes from each page, and these embeddings are then passed to a classifier. After training, the model's performance is assessed based on its ability to nominate elements. In nomination, the task is to identify a specific element from a given class on each page. For instance, the cart button is nominated by applying the trained model to every node on the page to obtain classification scores. These scores are then ranked, and the node with the highest cart score is nominated as the cart element.

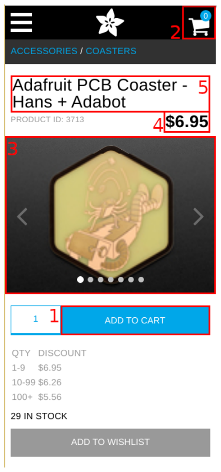


Figure 2: A sample webpage in our dataset with 748 nodes. The labeled elements are surrounded by red boxes. (1) is the *buy button*, (2) is the *cart button*, (3) is the *image*, (4) is the *price* and (5) is the product *name*.

To excel at the cart button nomination task, the classifier must consequently assign the highest cart score to the true cart element relative to all other elements on the page.

Element nomination is particularly challenging on realistic pages. A perfect classifier, which always assigns the correct class to every element, would also always nominate the correct element on every page. Hence, the classification objective serves as a proxy for training on the nomination task. However, the pages in our dataset consist of thousands of elements, and among these, there is a single labeled element for each class. For instance, a classifier with 99% accuracy would be expected to incorrectly classify 10 elements as 'add-to-cart' buttons on a page with $1,000$ elements, even though only one true 'add-to-cart' button exists. Consequently, in Section 6.5, we propose an effective, novel training method that improves the element nomination performance by steering the classification training objective closer towards the nomination objective.

4 Related work

In the literature, there is an unfortunate scarcity of datasets suitable for web element nomination. In this section, we walk through and compare existing datasets to the Klarna Product Page Dataset.

The minimalistic World-of-bits environment (Shi et al., 2017b), known as Mini-WoB, is useful for task-solving on the Web. However, the pages in Mini-WoB are simple compared to sites found on the Internet. A page in Mini-WoB might, for instance, consist of just a single form and a submit button. In contrast, the Klarna Product Page Dataset comprises manually annotated clones of real webpages, with the median page featuring $1,308$ elements and thousands of lines of code. The recently proposed WebShop (Yao et al., 2022) is another simulated interactive environment where agents can learn to navigate an e-commerce store and make purchases based on text instructions. WebShop includes 1.18 million products and $12,087$ text instructions. While it effectively emulates an e-commerce store, its primary limitation is that it comprises pages from a single website.

There are datasets related to ours that are useful for web content extraction, perhaps the most well-known being the SWDE dataset (Hao et al., 2011). This dataset comprises $124,291$ real webpages, each with $3-5$ labeled attributes, from 80 different websites across 8 verticals, such as online bookstores and camera retailers. Previous studies on SWDE (Lin et al., 2020; Zhou et al., 2021) have observed that test accuracy improves with the number of sites included in the training set for each vertical. However, the SWDE dataset is limited by having only 10 sites per vertical, thereby capping the potential gains. In comparison, our dataset consists of $8,175$ diverse e-commerce websites, and thus provides a much more comprehensive representation of a vertical. Furthermore, Klarna Product Page Dataset encompasses labels that present a wider range of learning challenges. Whereas the SWDE dataset solely contains labeled leaf nodes, which are often identifiable based on local information, our dataset includes labels where local information alone is insufficient for accurate identification. Elements like the *price* and *name*, for instance, are primarily defined by local information, making their identification similar to standard web data extraction tasks. Conversely, correctly identifying the *buy* button often requires both local and contextual information. Lastly, the *subject node* has no meaning on its own and can only be represented based on its context. Lastly, unlike the SWDE dataset, which contains only English pages, our dataset includes pages with text written in multiple languages.

A recent large-scale webpage dataset that signifies a substantial advancement over previous works is Mind2Web (Deng et al., 2023). Mind2Web encompasses 137 websites across 31 diverse domains, such as Music, Airlines, Housing, and Social Media. Consequently, it offers a valuable opportunity to assess generalizability across various tasks and domains. Our dataset complements Mind2Web in this aspect, as Klarna Product Page Dataset enables the assessment of generalizability for the same task across a large number of websites.

Overall, we firmly believe that the diverse range of webpage structures and labels in our dataset marks a significant advancement over current SOTA datasets for web element nomination. However, we wish to emphasize that having access to a variety of datasets, each with different challenges and contexts, is invaluable. Such diversity is crucial for advancing toward truly autonomous and generalizable web agents.

5 Embedders for DOM Elements

We now describe the GNN embedders that we train together with a classification layer (see Fig 3) on our dataset. The embedders represent three GNN families, specifically recurrent, convolutional and attention-based networks. We now detail and then evaluate these embedders in the simulation section.

GCN-Mean. we first consider a multi-layer GCN model inspired by GraphSage (Hamilton et al., 2017) and PinSage (Ying et al., 2018). Each convolutional layer ℓ, computes the representation of the current node, v, as $\mathbf{z}_v^{(\ell)}$ based on the local encoding and an average encoding $\mathbf{h}^{(\ell)}$ of its immediate neigborhood $\mathcal{N}(v)$. The representation is obtained according to the following:

$$\begin{aligned}
\mathbf{h}_v^{(\ell)} &= \text{AVG}\left(\{\text{ReLU}(\mathbf{V}_l \mathbf{z}_u^{(\ell-1)} + \mathbf{b}_l),\ u \in \mathcal{N}(v)\}\right), \\
\mathbf{k}_v^{(\ell)} &= \text{ReLU}\left(\mathbf{W}_l \cdot \text{CONCAT}(\mathbf{z}_v^{(\ell-1)}, \mathbf{h}_v^{(\ell)}) + \mathbf{w}_\ell\right), \\
\mathbf{z}_v^{(\ell)} &= \mathbf{k}_v^{(\ell)} / \left\|\mathbf{k}_v^{(\ell)}\right\|_2,
\end{aligned} \tag{1}$$

where $\mathbf{V}_l$, $\mathbf{W}_l$, $\mathbf{b}_l$ and $\mathbf{w}_l$ are trainable weight matrices for convolution layer ℓ and $\mathbf{z}_i^{(0)} = \mathbf{x}_i^{(0)}$ for all i. We use the same dimension for the encodings $\mathbf{h}_v^{(\ell)}$ and $\mathbf{k}_v^{(\ell)}$. Encoding size, representation size, and total number of layers are tunable hyperparameters. By stacking K convolution layers, information can be propagated from K-hop neighborhoods.

TransformerEncoder. This model consists of a single-layer multi-headed attention encoder stack (Vaswani et al., 2017) fed with a sequence consisting of the features $\mathbf{x}_v$ of the local node, v, stacked with the features $\mathbf{x}_u$ of its neighbors $u \in \mathcal{N}(v)$. The embedding $\mathbf{z}_v$ of node v is then extracted as the first element (here, at index 0) of the sequence $\mathbf{H}_v$ computed by the transformer encoder stack:

$$\mathbf{H}_v = \text{TransformerEncoder}\big(\text{STACK}\left(\mathbf{x}_v, \{\mathbf{x}_u,\ u \in \mathcal{N}(v)\}\right)\big), \quad \mathbf{z}_v = \mathbf{H}_v[0].$$

In our implementation, the number of heads in the encoder and the embedding size are tunable hyperparameters.

We excluded positional encodings from this model, as they negatively impacted the transformer's performance. We explored several types of positional encodings, initially formulating them by traversing the DOM tree using both depth-first and breadth-first search orders. Additionally, we attempted, albeit unsuccessfully, to train a general, powerful, and scalable graph transformer (GraphGPS) (Rampášek et al., 2023) using Laplacian eigenvector positional encodings.

The ineffectiveness of positional encodings in element nomination might be due to the considerable variation in DOM tree structures across different websites. In our dataset, the number of nodes varies from a few hundred to approximately 20,000. However, a more consistent representation of page structure could be explored in future work by considering the positions of node elements in their corresponding rendered screenshots. For example, a screenshot of a page on an iPhone X device will have a consistent width across websites, and the position of elements in the screenshot tends to remain stable (e.g., the "go to cart" button is typically located in the upper right corner). This stability would make the position in the screenshot a more consistent and meaningful positional representation compared to the position in the DOM tree.

Tree-LSTMs. We consider four tree-based LSTMs. They all revolve around a standard LSTM cell (Hochreiter & Schmidhuber, 1997) and are characterized by how the input sequence is constructed from the DOM tree.

In the top-down model (LSTM-TD), the embedding $\mathbf{z}_v^D$ of node v is the last element of the LSTM encoding of the path from the root to node v: each unit receives hidden and cell states from its parent, according to

$$\mathbf{h}_v^D, \mathbf{c}_v^D = \text{LSTM}(\mathbf{x}_v, \mathbf{h}_{\text{Parent}(v)}^D, \mathbf{c}_{\text{Parent}(v)}^D), \quad \mathbf{z}_v^D = \mathbf{h}_v^D.$$

where $\text{LSTM}(x, h, c)$ denotes a standard LSTM cell with input x, hidden state h and cell state c. Cell and hidden states were initialized as zero for the root node.

In the bottom-up model (LSTM-BU), we consider the child-sum tree-LSTM algorithm (Tai et al., 2015). Here, the sequence is defined recursively from the leaves to each node v. At each node, the hidden state is the sum of the hidden states of the children, and the cell state is computed based on the cell states of the children, with one forget gate per child state.

$$\mathbf{h}_v^U, \mathbf{c}_v^U = \text{ChildSumLSTM}\big(\mathbf{x}_v, \{\mathbf{h}_u^U,\, u \in \mathcal{C}(u)\}, \big\{\mathbf{c}_u^U,\, u \in \mathcal{C}(u)\big\}\big), \quad \mathbf{z}_v^U = \mathbf{h}_v^U.$$

To account for more context when computing the element embeddings, we combined the bottom-up and top-down approaches into a bidirectional model (LSTM-Bi) where the embeddings are the concatenation of the two previous models' embeddings, $\mathbf{z}_v^B = \text{CONCAT}(\mathbf{z}_v^D, \mathbf{z}_v^U)$. In this case, the weights in the top-down and the bottom-up components are trained simultaneously.

Finally, we considered a global bidirectional model (LSTM-BiE) that computes node representations based on the whole DOM-tree (Cook, 2019). This method has three steps. First, a bottom-up representation $\mathbf{z}_v^U$ is calculated for each node v. Second, this representation is then used as the input to a top-Down architecture that gives a representation $\mathbf{z}_v^E$ for each node v:

$$\mathbf{h}_v^E, \mathbf{c}_v^E = \text{LSTM}(\mathbf{z}_v^U, \mathbf{h}_{\text{Parent}(v)}^E, \mathbf{c}_{\text{Parent}(v)}^E), \qquad \mathbf{z}_v^E = \mathbf{h}_v^E.$$

Third, the two representations are concatenated into a final representation for the node $\mathbf{z}_v^{BiE} = \text{CONCAT}(\mathbf{z}_v^E, \mathbf{z}_v^U)$. Also, in this case, the weights in both components are trained simultaneously.

GCN-GRU. This model is inspired by the local embedding module in the DOM-Q-Net algorithm (Jia et al., 2019). Here, the encoding of node v is computed by feeding a Gated Recurrent Unit (GRU) with the local features of the node and an average encoding of the neighborhood of the node; then, the embedding is computed with a transformation of the local encoding $\mathbf{h}_v$ and the input features:

$$\begin{aligned} \mathbf{h}_v &= \text{GRU}\big(\mathbf{x}_v,\, \text{AVG}\big(\{\mathbf{V}\mathbf{x}_u + \mathbf{b},\, u \in \mathcal{N}(u)\}\big)\big), \\ \mathbf{z}_v &= \mathbf{W} \cdot \text{CONCAT}(\mathbf{x}_v,\, \mathbf{h}_v) + \mathbf{w}, \end{aligned}$$

where $\mathbf{V}$, $\mathbf{b}$, $\mathbf{W}$, and $\mathbf{w}$, are trained together with the parameters of the GRU.

FreeDOM. We adapt the FreeDOM architecture (Lin et al., 2020). This is a two-stage method where a neural network first computes node representations based on local and contextual information (using both text and HTML), and then uses representation distances and semantic relatedness between node pairs in the second stage. In the original implementation, (Lin et al., 2020) perform a filtering step where templates common to multiple pages are identified and used to reduce the number of nodes that the model considers. On our dataset, this is not possible since the pages generally do not come from the same set of websites. That being said, FreeDOM may be at a disadvantage compared to the other models because it does not perfectly suit our application or dataset. However, the authors set out to learn site-invariant feature representations and found that FreeDOM could generalize well to unseen websites.

6 Element Nomination Evaluation

As a starting point for research on the Klarna Product Page Dataset, we now compare various GNNs on the nomination task. To that effect, we first describe the common experimental setup in Section 6.1 and then present the results of this empirical evaluation in the following sections. These results first include the nomination accuracies from the Basic Training Procedure in Section 6.2. Next, we use the best-performing model from the initial evaluation to filter out most elements from the webpages and further refine our nomination results by applying GPT-4 to the HTML content of the filtered elements in Section 6.3. In Section 6.4, we conduct a sensitivity analysis on the best-performing GNN to investigate whether it suffers from over-smoothing and over-squashing. Lastly, we demonstrate that the CNTP training scheme significantly boosts nomination performance in Section 6.5.

6.1 Experimental Setup

Training Procedures. During training, the models learn to classify elements using the DOM tree representation of a page. More specifically, a GNN embedder takes a node with some neighborhood as input, and

Table 2: The nomination accuracy of each model on each label without (left) and with text (right) added to the element features.

	buy btn		cart btn		main img		name		price		subj		avg	
Model	w/o	w/	w/o	w/	w/o	w/	w/o	w/	w/o	w/	w/o	w/	w/o	w/
LSTM-Bi*	.72	-	.57	-	.47	-	.69	-	.48	-	.66	-	.60	-
LSTM-BiE*	.73	-	.60	-	.50	-	.72	-	.55	-	.70	-	.63	-
GCN-GRU	.77(.01)	.83(.003)	.57(.005)	.62(.003)	.41(.006)	.38(.004)	.69(.001)	.79(.003)	.50(.02)	.60(.003)	.45(.003)	.53(.003)	.56	.63
FreeDOM**	-	.29(.09)	-	.056(.04)	-	.043(.02)	-	.57(.07)	-	.23(.03)	-	.35(.02)	-	.26
FreeDOM-ext**	-	.84(.01)	-	.59(.007)	-	.31(.01)	-	.84(.01)	-	.72(.02)	-	.46(.02)	-	.63
LSTM-TD	.71(.02)	.85(.04)	.50(.02)	.51(.02)	.42(.02)	.46(.02)	.70(.01)	.76(.00)	.52(.004)	.58(.03)	.59(.02)	.34(.01)	.57	.58
LSTM-BU	.73(.06)	.89(.03)	.57(.03)	.65(.02)	.45(.03)	.44(.02)	.69(.02)	.74(.01)	.46(.06)	.53(.02)	.66(.02)	.56(.02)	.59	.64
TE	.69(.02)	.81(.01)	.43(.03)	.46(.04)	.25(.06)	.34(.02)	.73(.03)	.79(.01)	.60(.03)	.62(.09)	.55(.03)	.62(.09)	.54	.61
FCN	.79(.01)	.86(.01)	.53(.004)	.62(.009)	.32(.03)	.27(.003)	.70(.01)	.85(.01)	.58(.09)	.61(.01)	.43(.04)	.39(.01)	.56	.60
GCN-Mean	.78(.04)	.91(.004)	.62(.005)	.67(.03)	.61(.02)	.48(.01)	.78(.004)	.81(.002)	.66(.02)	.66(.004)	.84(.01)	.86(.002)	.71	.73
REVGNN - 20 layer	**.81**	-	**.65**	-	**.62**	-	**.79**	-	**.66**	-	**.89**	-	**.74**	-

its output is then classified by a single-layer fully connected neural network (see Fig 3 and Section 3). The classification gives rise to a cross-entropy training objective that is minimized using Adam. Furthermore, due to the large class imbalance between the six labeled nodes and the potentially thousands of unlabeled nodes on a page, we cannot train on all nodes of a page. In the *Basic Nomination Training Procedure*, presented in Section 6.2, every model instead classifies five labeled and ten randomly sampled unlabeled DOM elements from each page. In the *Challenge Nomination Training Procedure*, presented in Section 6.5, we conduct an additional experiment where we train on labeled nodes and unlabeled negative examples that the models confidently misclassified. Information regarding hyper-parameters can be found in Section A.1.

Embedders. We use embedders from three important GNN families, specifically recurrent, convolutional, and attention-based networks. Specifically, we consider LSTM-based embedders (LSTM-TD, LSTM-BU, LSTM-Bi, LSTM-BiE), the mean-pooled GCN model (GCN-Mean), the GRU-based GCN inspired by DOM-Q-Net (GCN-GRU), a 20 layer and 2 group RevGNN and the transformer-encoder (TE).[4] We also include a 20-layer, 2-group RevGNN model, which uses the GCN-Mean model as its base GNN. For comparison, we also present the results of the SOTA FreeDOM architecture, which we train on two different sets of features. First, we use the original features defined in (Lin et al., 2020), and then we specify an extended version (FreeDOM-ext) which, in addition, uses the style features employed by our other models (see the next paragraph). We also implement a 2-layer *Fully Connected Network (FCN)* that only looks at the features of a local node without considering any neighbors, thus acting as a context-oblivious baseline. After training, we evaluate how accurately the GNNs can nominate the six labels described in Section 2.

Features. For each node's *local features*, we define a set of *style features* which consists of the bounding box of the elements as rendered on the page, font weight, font size, number of images contained within the subtree, visibility, and HTML tag. For the FreeDOM-specific, pre-trained, NLP features described in (Lin et al., 2020), we use the Spacy[5](Honnibal et al., 2020) library. To also gauge the impact of textual features on the other models, we perform an experiment where we create an additional feature by embedding the text of a web element using the *Universal Sentence Encoder*[6] (Cer et al., 2018). FreeDOM's implementation stays the same in this experiment as it already uses text.

6.2 Basic Training Procedure

Setup. In this comparison we trained the models on a subset of the Klarna Product Page Dataset containing $10,000$ pages from English markets. We did not train the models on the entire dataset because the LSTM models are very computationally expensive. It also offers a more level playing field for the SOTA FreeDOM architecture, since it relies on page text and was originally applied to English websites.

[4]We would also like to address the absence of the very popular Graph Attention Network (GAT) from our evaluation. Despite investing significant effort in training various versions of GAT on our dataset, its performance was consistently inferior to the other models we assessed. Consequently, we decided to exclude GAT from our evaluation.

[5]v2.3.5 *en_core_web_sm* https://spacy.io/models/en (MIT License)

[6]Version 4, https://tfhub.dev/google/universal-sentence-encoder/4 (Apache-2.0 License)

Evaluation. The trained models are evaluated based on their nomination performance. As described in Section 3, with the exception of FreeDOM, we compute the nomination metric by classifying all nodes on every webpage in the test set. These scores are used to rank the nodes for each of the classes: *price*, *name*, *image*, *buy button*, *cart button*, and *subject node*. The node with the highest score for each class is nominated for that class. A nomination is considered correct if the nominated element is the single element with the ground truth label. For FreeDOM, we followed the protocol described in (Lin et al., 2020). The evaluation is performed on $6,706$ test pages from merchants not present in the training set.

6.2.1 Results

Nomination Accuracy. Table 2 contains the nomination results. Note that here precision and recall both equal accuracy as the methods make exactly one prediction on each page, and there is one correct element per class. From the results with only style features (no text features), we first notice that GCN-Mean achieves the highest average accuracy by a wide margin (6.8 p.p.). Despite its relative simplicity, GCN-Mean consistently scores among the best for all tasks explored here. Since GCN-Mean uses k-hop neighborhoods (see Section 5), this suggests that a large proportion of the context relevant for element nomination is concentrated in an element's vicinity. The RevGNN algorithm successfully builds upon the GCN-Mean algorithm, leading to further improvements in the final nomination accuracy. Among the runner-ups, LSTM-BiE stands out, as it shows similar performance to FreeDOM-ext (using text), while GCN-GRU, LSTM-TD, LSTM-Bi and LSTM-BU all show similar average performance. It is worth noting that FreeDOM requires two separate training stages and that the LSTMs require substantially more compute than GCN-Mean, GCN-GRU and FreeDOM.

Classification Accuracy. The classification accuracy of the models considered here are presented in Section A.5. Despite all models achieving very high and similar classification scores, their nomination performance differs substantially. This illustrates the discrepancy between the classification training objective and the nomination evaluation task. We address this discrepancy using CNTP, which we present further below.

The Impact of Contextual Information on Nomination. We found that more context helps performance on certain tasks. As an indicator of the importance of context, we consider the performance of the FCN. Specifically, since the FCN only looks at a local node's features without including information from neighbors, the gap between the best model and the FCN gives us a lower bound on the gain we can achieve by including contextual information. With this contextual importance indicator, it is possible to identify tasks where contextual information is more important. For example, the *subject node* on its own does not contain much information but is instead defined by its relationship to other nodes in the tree; therefore, we need to look at its context to identify it. For other tasks, context is less important. For example, the *buy button* seemingly contains sufficient information to be correctly identified based on its local features. Finally, another interesting observation related to context is that LSTM-BiE outperforms LSTM-Bi on all tasks, indicating that processing all context from the page improves accuracy.

The Impact of Text on Nomination. When we add text features, GCN-Mean still has the highest average accuracy, this time by an even wider margin. Though LSTM-BiE was not trained with text due to computational constraints, its performance remains competitive with all other algorithms except GCN-Mean when trained on solely style features. This further solidifies our intuition that straightforward graphical algorithms such as GCN-Mean and LSTM-BiE should be explored further as building blocks in web element nomination algorithms. Furthermore, one important benefit of LSTM-BiE and GCN-Mean over FreeDOM, SimpDOM, and WebFormer is that they remain competitive without text features. This allows us to deploy a single model that can be used across webpages, regardless of the language used on the page.

Another important finding is that algorithms that try to exploit text perform worse when this information is irrelevant to the task. We can observe this degradation when GCN-Mean, GCN-GRU, and even FCN attempt to use text to nominate the image node. LSTM-TD performance drops when text is added to its feature set since it looks at the text in nodes above the *subject node*. The *subject nodes* are usually close to the root of the DOM tree; hence, it is unlikely that nodes in the considered sequence even contain text. This variety in performance suggests that we need varying degrees of contextual information to nominate different label types. This also suggests that the Klarna Product Page Dataset presents a comprehensive set of challenges that not all algorithms can easily overcome.

6.3 Post Training LLM Refinement

Setup. The refinement step was initiated by filtering out all non-informative elements from the test set using the trained 20-layer RevGNN algorithm from Section 6.2. This filtering was performed by ranking the elements by their classification scores and retaining the ten highest-ranked elements. The raw HTML of these elements, combined with their bounding boxes, was then used to formulate a query where the task was to select the single labeled element from the set of elements. We then presented this query to GPT-4, which performed the final nomination by providing an answer to the query. This experiment was constrained to 500 randomly sampled English pages from the test set.

Results. From the results shown in Figure 4, it is evident that the LLM refinement step substantially enhances the final nominations, despite relying solely on local element content. It significantly boosts the nomination performance across all tasks, resulting in an average nomination accuracy increase of 10.9 percentage points. The improvement is particularly noticeable for the product image element, indicating that the raw HTML contains substantial information for this specific task. However, there is still room for improvement, which could potentially be achieved by incorporating screenshots of the rendered pages.

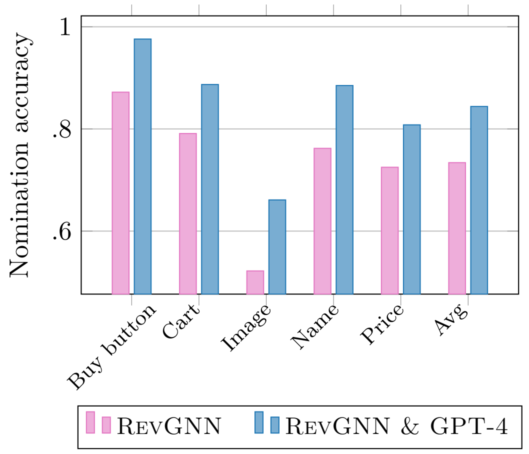


Figure 4: **Substantially Enhanced Nomination Accuracy by Combining RevGNN with GPT-4:** The performance of the RevGNN algorithm alone versus its performance when combined with a GPT-4-based refinement step. In the enhanced scenario, the RevGNN algorithm initially filters the dataset to retain only the top 10 elements with the highest classification scores on each page. Subsequently, GPT-4 undertakes the final nomination step, based on the local HTML content of these selected elements. This refinement step significantly boosts nomination accuracy across all tasks, resulting in an average increase of 10.9 percentage points.

6.4 Sensitivity Analysis

Simple message-passing GNNs may suffer from over-smoothing and over-squashing, where information flow between distant nodes becomes distorted (Topping et al., 2021). This distortion can negatively impact the model's performance in tasks that rely on long-range interactions, such as element nomination, where critical information may be located far from the root in large trees. To assess whether the GCN-Mean algorithm is prone to these issues, we conducted a sensitivity analysis on a subset of 8,000 pages, gradually increasing the number of layers, as shown in Table 3. The results indicate that while the GCN's performance initially improves with more layers, it begins to degrade after adding a third layer, suggesting the presence of over-smoothing and over-squashing effects.

One potential approach to mitigating these effects is graph rewiring, where the DOM-tree is modified to enhance information flow. A particularly promising method that could be explored in future work is Expander Graph Propagation (Deac et al., 2022), which augments the DOM-tree with expander graphs. These graphs, despite their sparsity, ensure efficient message passing throughout the entire structure, enabling information to propagate quickly and effectively. This approach could be well-suited for managing the complexities of large DOM-trees, where critical information may be dispersed across the tree.

6.5 Challenge Nomination Training Procedure - Bridging the *classification* and *nomination* objectives

We put forth CNTP, a novel two-stage training approach which is similar to the method in Ben-Baruch et al. (2022) and inspired by Positive-Unlabelled Learning (see Bekker & Davis (2020) for a survey). In CNTP, we

No. Layers	1	2	3	4
Avg Nomination Accuracy	0.649	0.679	0.666	0.631

Table 3: Sensitivity analysis results from varying the number of layers in the GCN-Mean Algorithm.

train on the classification objective, which means that we only need to train on a small subset of elements from each page in the training set. We then periodically rank the elements on the page based on their classification scores and add the confusing elements to the training set. We define a confusing element as an unlabeled element that inaccurately receives a very high score for a particular label. This procedure increases the likelihood that the true labeled elements appear at the top of the ranking during the nomination phase.

Notation. The parameters of CNTP are: M, the number of unlabeled elements to be randomly included in the training set from each page; T, the number of training epochs; and K, the number of additional *hard* elements identified by the model in the nomination task after T epochs.

CNTP. The pseudo-code for the training data augmentation step is presented in Algorithm 1. A description of the procedure goes as follows: At the start of every epoch, we begin with an empty training set of elements $S_{train} = \varnothing$. For each webpage $P \triangleq (V, E)$, where V is the set of elements in the training set $\mathcal{P}$, we uniformly sample a set $S_P = \{v_i \in V_{unlabelled} : i = 1, \ldots, M\}$ of M unlabeled elements. We add S_P to the classifier's training set, along with all L labeled elements: $S_{train} = \bigcup_{P \in \mathcal{P}} (S_P \cup V_{labelled})$. We then train the model for one epoch. At epoch T, we evaluate the model on the nomination task across the entire set $\mathcal{P}$ and initialize the sets of *hard* training examples, $H_P = \varnothing$ for all $P \in \mathcal{P}$. Then, for all $P \in \mathcal{P}$, we add the top K unlabeled elements in the proposed ranking for each of the L labels to H_P. It is sufficient to perform this step once. For all future epochs, these elements are always considered additional training examples in the classification task: $S_{train} = \bigcup_{P \in \mathcal{P}} (H_P \cup S_P \cup V_{labelled})$. Thus, we train on $M + L \times K$ unlabeled elements and all the labeled ones. Note that, as opposed to Ben-Baruch et al. (2022), we attach the *negative* label to these nodes.

CNTP offers two main benefits: 1) it uses only a small fraction of the total elements in the training set, and 2) it bridges the gap between the nomination and classification tasks. The first benefit allows us to avoid the impractical computational cost of training to rank all elements, focusing only on the top candidates instead of those confidently identified as uninteresting. The second benefit is achieved by training on more confusing unlabeled elements—those likely to appear high in the nomination ranking. This approach aids the model in distinguishing between the ground truth elements and the uninteresting elements that receive high scores.

6.5.1 Results

Here we use the entire dataset with pages from all markets, with $M = 20$, $K = 5$, $T = 50$, and $L = 6$.

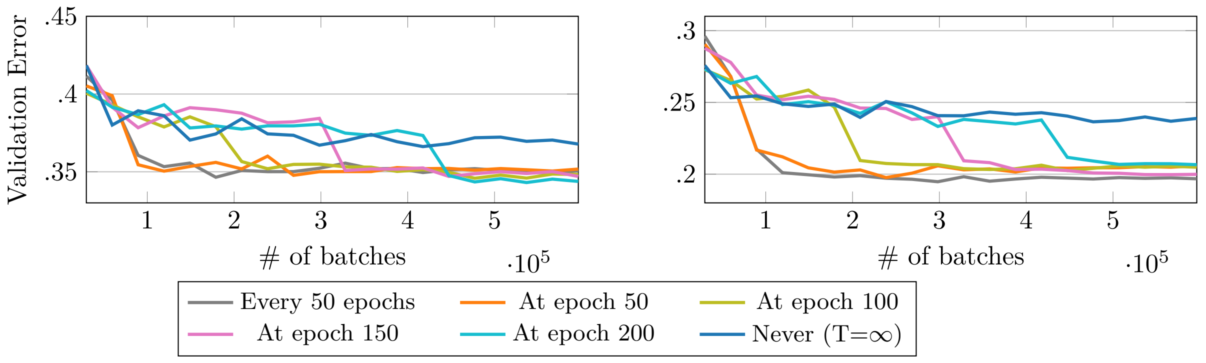


Figure 5: Effect on average validation error from performing the augmentation step at different times, consistently, and not at all for FCN (left) and GCN-Mean (right).

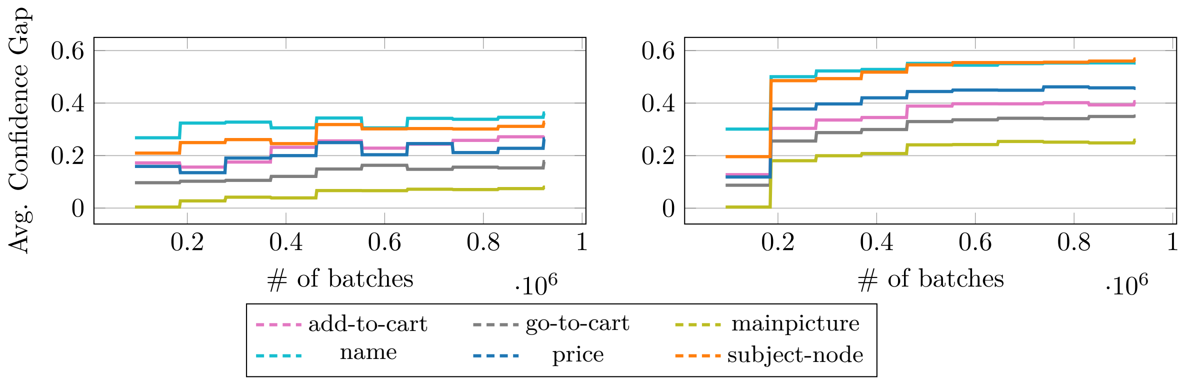


Figure 6: Effect on the average *confidence gap* from using *hard examples* for GCN-Mean. The left plot shows the average confidence gaps during training without augmentation. On the right, we show the corresponding confidence gaps when the hard examples are added to the training set.

Effects on Nomination Accuracy. Figure 5 highlights the effect of the timing of the *hard example* augmentation step on the average nomination accuracy on the validation set while training the FCN and GCN-Mean. We observe that the timing of the augmentation makes little difference on the final nomination accuracy. This suggests that there are a few consistently confusing elements that can be relatively easily identified using models trained on randomly selected unlabeled elements as negatives. Once these elements are in the training set, the models' nomination performance improves significantly. Indeed, both FCN and GCN-Mean achieve lower errors after the augmentation, by about 2 and 5 percentage points, respectively, with GCN-Mean reaching beyond 80

Effects on the Quality of Rankings. We evaluate whether CNTP brings us closer to training directly on the nomination objective. As a proxy fort his, we measure the *confidence gap*: the difference between the confidence assigned to the labeled element and the highest confidence assigned to any unlabeled element on the same page. We assume that the larger this difference is, the *better* the resulting ranking will be. Since either unlabeled elements become less likely to be mistaken for the true element (when the true element is ranked first) or the difference by which an unlabeled element wins in the ranking (when the true element is not ranked first) is lower, and hence the ground-truth labeled element appears higher in the ranking.

In Figure 6, we ask the models to perform the nomination task on the entire training set every 50 epochs and measure the average confidence gap per class. From the basic classification objective, we observe that the confidence gap increases on average, yet this behaviour is far from monotonic. In contrast, when we add *hard examples* during training, the rankings that the nomination objective is based on gets steadily better when we add *hard examples* during training according to our metric. This performance more closely resembles what we would expect when optimizing directly for the nomination objective. In this experiment, augmentation is performed every 50 epochs, though the same behavior is observed when this step is performed only once.

7 Limitations

One shortcoming of the Klarna Product Page Dataset is that far from all elements have a ground truth label; we only have one label per class per page, which makes our results slightly pessimistic. In reality, a click event on several elements within the *buy button* (e.g., the button itself and the node containing the button text) could generate the same result. Thus, there are several acceptable nominations in practice. The *single label per element type* issue reduces the number of positive training examples in the training set and increases the difficulty of the nomination task. While this results in a lower overall accuracy than what would be achieved in practice, it should not affect the comparison between methods. Furthermore, perfectly annotating all nodes of each element in a dataset of this size is very challenging and would require substantial web development knowledge. One approach to reduce the stringency of the evaluation would be to check the content of nominated elements. However, this is not appropriate for action elements and requires resilient content extraction heuristics for all considered classes.

8 Conclusion

We introduce Klarna Product Page Dataset, a large-scale realistic dataset containing 51, 701 product pages from 8, 175 merchants across 8 markets, with labels that present varied challenges. To initiate research on our dataset, we explored the potential of GNNs for nominating webpage elements and how these methods could be combined with LLMs. Our experiments demonstrate the untapped potential of GNNs for web element nomination and illustrate how to effectively combine GNNs with LLMs for this purpose.

References

Jessa Bekker and Jesse Davis. Learning from positive and unlabeled data: A survey. *Machine Learning*, 109 (4):719–760, 2020.

Emanuel Ben-Baruch, Tal Ridnik, Itamar Friedman, Avi Ben-Cohen, Nadav Zamir, Asaf Noy, and Lihi Zelnik-Manor. Multi-label classification with partial annotations using class-aware selective loss. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 4764–4772, 2022.

Daniel Cer, Yinfei Yang, Sheng-yi Kong, Nan Hua, Nicole Limtiaco, Rhomni St. John, Noah Constant, Mario Guajardo-Cespedes, Steve Yuan, Chris Tar, Brian Strope, and Ray Kurzweil. Universal sentence encoder for English. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pp. 169–174, Brussels, Belgium, November 2018. Association for Computational Linguistics. URL https://www.aclweb.org/anthology/D18-2029.

Cedric Cook. Learning context-aware representations of subtrees. Master's thesis, Ecole Polytechnique Federale de Lausanne, Lausanne, 2019.

Glen Coppersmith. Vertex nomination. *Wiley Interdisciplinary Reviews: Computational Statistics*, 6(2): 144–153, 2014.

Andreea Deac, Marc Lackenby, and Petar Veličković. Expander graph propagation. In *Learning on Graphs Conference*, pp. 38–1. PMLR, 2022.

Xiang Deng, Yu Gu, Boyuan Zheng, Shijie Chen, Samuel Stevens, Boshi Wang, Huan Sun, and Yu Su. Mind2web: Towards a generalist agent for the web. *arXiv preprint arXiv:2306.06070*, 2023.

Donniell E Fishkind, Vince Lyzinski, Henry Pao, Li Chen, and Carey E Priebe. Vertex nomination schemes for membership prediction. *The Annals of Applied Statistics*, 9(3):1510–1532, 2015.

Hiroki Furuta, Kuang-Huei Lee, Ofir Nachum, Yutaka Matsuo, Aleksandra Faust, Shixiang Shane Gu, and Izzeddin Gur. Multimodal web navigation with instruction-finetuned foundation models, 2023.

Izzeddin Gur, Ofir Nachum, Yingjie Miao, Mustafa Safdari, Austin Huang, Aakanksha Chowdhery, Sharan Narang, Noah Fiedel, and Aleksandra Faust. Understanding html with large language models, 2023.

William L. Hamilton, Rex Ying, and Jure Leskovec. Inductive representation learning on large graphs. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, NIPS'17, pp. 1025–1035, Red Hook, NY, USA, 2017. Curran Associates Inc. ISBN 9781510860964.

Qiang Hao. Structured web data extraction dataset (swde). 2011. URL https://swde.codeplex.com/.

Qiang Hao, Rui Cai, Yanwei Pang, and Lei Zhang. From one tree to a forest: A unified solution for structured web data extraction. In *Proceedings of the 34th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pp. 775–784. ACM, 2011.

Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural Computation*, 9(8):1735–1780, 1997.

Matthew Honnibal, Ines Montani, Sofie Van Landeghem, and Adriane Boyd. spaCy: Industrial-strength Natural Language Processing in Python, 2020.

Sheng Jia, Jamie Ryan Kiros, and Jimmy Ba. DOM-Q-NET: Grounded RL on structured language. In *International Conference on Learning Representations*, 2019. URL https://openreview.net/forum?id=HJgd1nAqFX.

Geunwoo Kim, Pierre Baldi, and Stephen McAleer. Language models can solve computer tasks, 2023.

Anurendra Kumar, Keval Morabia, William Wang, Kevin Chang, and Alex Schwing. CoVA: Context-aware visual attention for webpage information extraction. In *Proceedings of The Fifth Workshop on e-Commerce and NLP (ECNLP 5)*, pp. 80–90, Dublin, Ireland, May 2022. Association for Computational Linguistics. URL https://aclanthology.org/2022.ecnlp-1.11.

Guohao Li, Matthias Müller, Bernard Ghanem, and Vladlen Koltun. Training graph neural networks with 1000 layers. In *International conference on machine learning*, pp. 6437–6449. PMLR, 2021.

Richard Liaw, Eric Liang, Robert Nishihara, Philipp Moritz, Joseph E Gonzalez, and Ion Stoica. Tune: A research platform for distributed model selection and training. *arXiv preprint arXiv:1807.05118*, 2018.

Bill Yuchen Lin, Ying Sheng, Nguyen Vo, and Sandeep Tata. Freedom: A transferable neural architecture for structured information extraction on web documents. *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, Jul 2020.

OpenAI, :, Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, Red Avila, Igor Babuschkin, Suchir Balaji, Valerie Balcom, Paul Baltescu, Haiming Bao, Mo Bavarian, Jeff Belgum, Irwan Bello, Jake Berdine, Gabriel Bernadett-Shapiro, Christopher Berner, Lenny Bogdonoff, Oleg Boiko, Madelaine Boyd, Anna-Luisa Brakman, Greg Brockman, Tim Brooks, Miles Brundage, Kevin Button, Trevor Cai, Rosie Campbell, Andrew Cann, Brittany Carey, Chelsea Carlson, Rory Carmichael, Brooke Chan, Che Chang, Fotis Chantzis, Derek Chen, Sully Chen, Ruby Chen, Jason Chen, Mark Chen, Ben Chess, Chester Cho, Casey Chu, Hyung Won Chung, Dave Cummings, Jeremiah Currier, Yunxing Dai, Cory Decareaux, Thomas Degry, Noah Deutsch, Damien Deville, Arka Dhar, David Dohan, Steve Dowling, Sheila Dunning, Adrien Ecoffet, Atty Eleti, Tyna Eloundou, David Farhi, Liam Fedus, Niko Felix, Simón Posada Fishman, Juston Forte, Isabella Fulford, Leo Gao, Elie Georges, Christian Gibson, Vik Goel, Tarun Gogineni, Gabriel Goh, Rapha Gontijo-Lopes, Jonathan Gordon, Morgan Grafstein, Scott Gray, Ryan Greene, Joshua Gross, Shixiang Shane Gu, Yufei Guo, Chris Hallacy, Jesse Han, Jeff Harris, Yuchen He, Mike Heaton, Johannes Heidecke, Chris Hesse, Alan Hickey, Wade Hickey, Peter Hoeschele, Brandon Houghton, Kenny Hsu, Shengli Hu, Xin Hu, Joost Huizinga, Shantanu Jain, Shawn Jain, Joanne Jang, Angela Jiang, Roger Jiang, Haozhun Jin, Denny Jin, Shino Jomoto, Billie Jonn, Heewoo Jun, Tomer Kaftan, Łukasz Kaiser, Ali Kamali, Ingmar Kanitscheider, Nitish Shirish Keskar, Tabarak Khan, Logan Kilpatrick, Jong Wook Kim, Christina Kim, Yongjik Kim, Hendrik Kirchner, Jamie Kiros, Matt Knight, Daniel Kokotajlo, Łukasz Kondraciuk, Andrew Kondrich, Aris Konstantinidis, Kyle Kosic, Gretchen Krueger, Vishal Kuo, Michael Lampe, Ikai Lan, Teddy Lee, Jan Leike, Jade Leung, Daniel Levy, Chak Ming Li, Rachel Lim, Molly Lin, Stephanie Lin, Mateusz Litwin, Theresa Lopez, Ryan Lowe, Patricia Lue, Anna Makanju, Kim Malfacini, Sam Manning, Todor Markov, Yaniv Markovski, Bianca Martin, Katie Mayer, Andrew Mayne, Bob McGrew, Scott Mayer McKinney, Christine McLeavey, Paul McMillan, Jake McNeil, David Medina, Aalok Mehta, Jacob Menick, Luke Metz, Andrey Mishchenko, Pamela Mishkin, Vinnie Monaco, Evan Morikawa, Daniel Mossing, Tong Mu, Mira Murati, Oleg Murk, David Mély, Ashvin Nair, Reiichiro Nakano, Rajeev Nayak, Arvind Neelakantan, Richard Ngo, Hyeonwoo Noh, Long Ouyang, Cullen O'Keefe, Jakub Pachocki, Alex Paino, Joe Palermo, Ashley Pantuliano, Giambattista Parascandolo, Joel Parish, Emy Parparita, Alex Passos, Mikhail Pavlov, Andrew Peng, Adam Perelman, Filipe de Avila Belbute Peres, Michael Petrov, Henrique Ponde de Oliveira Pinto, Michael, Pokorny, Michelle Pokrass, Vitchyr Pong, Tolly Powell, Alethea Power, Boris Power, Elizabeth Proehl, Raul Puri, Alec Radford, Jack Rae, Aditya Ramesh, Cameron

Raymond, Francis Real, Kendra Rimbach, Carl Ross, Bob Rotsted, Henri Roussez, Nick Ryder, Mario Saltarelli, Ted Sanders, Shibani Santurkar, Girish Sastry, Heather Schmidt, David Schnurr, John Schulman, Daniel Selsam, Kyla Sheppard, Toki Sherbakov, Jessica Shieh, Sarah Shoker, Pranav Shyam, Szymon Sidor, Eric Sigler, Maddie Simens, Jordan Sitkin, Katarina Slama, Ian Sohl, Benjamin Sokolowsky, Yang Song, Natalie Staudacher, Felipe Petroski Such, Natalie Summers, Ilya Sutskever, Jie Tang, Nikolas Tezak, Madeleine Thompson, Phil Tillet, Amin Tootoonchian, Elizabeth Tseng, Preston Tuggle, Nick Turley, Jerry Tworek, Juan Felipe Cerón Uribe, Andrea Vallone, Arun Vijayvergiya, Chelsea Voss, Carroll Wainwright, Justin Jay Wang, Alvin Wang, Ben Wang, Jonathan Ward, Jason Wei, CJ Weinmann, Akila Welihinda, Peter Welinder, Jiayi Weng, Lilian Weng, Matt Wiethoff, Dave Willner, Clemens Winter, Samuel Wolrich, Hannah Wong, Lauren Workman, Sherwin Wu, Jeff Wu, Michael Wu, Kai Xiao, Tao Xu, Sarah Yoo, Kevin Yu, Qiming Yuan, Wojciech Zaremba, Rowan Zellers, Chong Zhang, Marvin Zhang, Shengjia Zhao, Tianhao Zheng, Juntang Zhuang, William Zhuk, and Barret Zoph. Gpt-4 technical report, 2023.

Ladislav Rampášek, Mikhail Galkin, Vijay Prakash Dwivedi, Anh Tuan Luu, Guy Wolf, and Dominique Beaini. Recipe for a general, powerful, scalable graph transformer, 2023. URL https://arxiv.org/abs/2205.12454.

Tianlin Shi, Andrej Karpathy, Linxi Fan, Jonathan Hernandez, and Percy Liang. World of bits: An open-domain platform for web-based agents. In Doina Precup and Yee Whye Teh (eds.), *Proceedings of the 34th International Conference on Machine Learning*, volume 70 of *Proceedings of Machine Learning Research*, pp. 3135–3144. PMLR, 06–11 Aug 2017a. URL https://proceedings.mlr.press/v70/shi17a.html.

Tianlin Shi, Andrej Karpathy, Linxi Fan, Jonathan Hernandez, and Percy Liang. World of bits: An open-domain platform for web-based agents. In *International Conference on Machine Learning*, pp. 3135–3144. PMLR, 2017b.

Kai Sheng Tai, Richard Socher, and Christopher D. Manning. Improved semantic representations from tree-structured long short-term memory networks. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pp. 1556–1566, July 2015.

Jake Topping, Francesco Di Giovanni, Benjamin Paul Chamberlain, Xiaowen Dong, and Michael M Bronstein. Understanding over-squashing and bottlenecks on graphs via curvature. *arXiv preprint arXiv:2111.14522*, 2021.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in neural information processing systems*, pp. 5998–6008, 2017.

Lei Wang, Chen Ma, Xueyang Feng, Zeyu Zhang, Hao Yang, Jingsen Zhang, Zhiyuan Chen, Jiakai Tang, Xu Chen, Yankai Lin, Wayne Xin Zhao, Zhewei Wei, and Ji-Rong Wen. A survey on large language model based autonomous agents, 2023.

Qifan Wang, Yi Fang, Anirudh Ravula, Fuli Feng, Xiaojun Quan, and Dongfang Liu. Webformer: The web-page transformer for structure information extraction. In *Proceedings of the ACM Web Conference 2022*, WWW '22, pp. 3124–3133, New York, NY, USA, 2022. Association for Computing Machinery. ISBN 9781450390965. doi: 10.1145/3485447.3512032. URL https://doi.org/10.1145/3485447.3512032.

Shunyu Yao, Howard Chen, John Yang, and Karthik Narasimhan. Webshop: Towards scalable real-world web interaction with grounded language agents. *arXiv preprint arXiv:2207.01206*, 2022.

Shunyu Yao, Howard Chen, John Yang, and Karthik Narasimhan. Webshop: Towards scalable real-world web interaction with grounded language agents, 2023.

Rex Ying, Ruining He, Kaifeng Chen, Pong Eksombatchai, William L Hamilton, and Jure Leskovec. Graph convolutional neural networks for web-scale recommender systems. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pp. 974–983, 2018.

Andrew Zhao, Daniel Huang, Quentin Xu, Matthieu Lin, Yong-Jin Liu, and Gao Huang. Expel: Llm agents are experiential learners, 2023.

Boyuan Zheng, Boyu Gou, Jihyung Kil, Huan Sun, and Yu Su. Gpt-4v (ision) is a generalist web agent, if grounded. *arXiv preprint arXiv:2401.01614*, 2024.

Longtao Zheng, Rundong Wang, and Bo An. Synapse: Leveraging few-shot exemplars for human-level computer control, 06 2023.

Yichao Zhou, Ying Sheng, Nguyen Vo, Nick Edmonds, and Sandeep Tata. Simplified DOM trees for transferable attribute extraction from the web. *CoRR*, abs/2101.02415, 2021. URL https://arxiv.org/abs/2101.02415.

A Appendix

A.1 Hyper-Parameters

We ensured that all hyper-parameters were optimized for this setting. For FreeDOM, we used the hyper-parameters provided by the original paper since our setting is very similar. For the TreeLSTM-based algorithms, we used the results of the hyper-parameter tuning in Cook (2019). We then performed hyper-parameter tuning for GCN-Mean, GCN-GRU, FCN and the TransformerEncoder. We tuned our method and these other particular algorithms since we have adapted and applied them to a substantially different setting than what they were designed for. In the tuning procedure, we performed a grid-search over the values in HYPERPARAMETER_GRIDS folder[7] using the RAY TUNE (Liaw et al., 2018) library.

A.2 Bridging Classification and Nomination

Algorithm 1 details the procedure we follow for augmenting the sample of web elements used in training on the classification objective for it to better resemble optimisation on the nomination task. In Figure 7, we can see the evolution of the average confidence assigned to the true labelled elements (continuous lines) versus the average maximal confidence assigned to any unlabelled element (dashed lines). We can clearly notice the distance between these quantities increasing dramatically after the augmentation step at epoch 50 and also, them continuing to diverge as training continues.

Algorithm 1 Hard-Example Augmentation

```
1: Inputs: $M, K, \epsilon, \mathcal{P}$ (the page dataset)
2: $H_P := \varnothing, \forall P \in \mathcal{P}$
3: nn_model := model_init()
4: for $epoch = 1, 2, \ldots$ do
5:     $S_{train} := \varnothing$
6:     for each webpage $P \in \mathcal{P}$ do
7:         $P \triangleq (V, E)$, $V \triangleq V_{labelled} \cup V_{unlabelled}$
8:         $S_P :=$ UniformRand($V_{unlabelled}$, $\text{n}_{\text{samples}} = M$)
9:         if $epoch = K$ then
10:            for $l := 1, \ldots, L$ do
11:                $preds = \{\text{nn\_model}(v)[l], \forall \text{elements } v \in V\}$
12:                $H_P := H_P \cup \text{rank}(preds)[: K]$
13:            end for
14:        end if
15:        $S_{train} := S_{train} \cup S_P \cup V_{labelled} \cup H_P$
16:    end for
17:    Train nn_model for 1 epoch on dataset $S_{train}$.
18: end for
```

A.3 Nomination Accuracy Results

In Figure 8 we present a graphical representation of the nomination accuracy results in Table 2. In this representation, in order to better visualise the impact of text features, the performance of an algorithm when using text features and not, are overlaid: full bars represents performance without text features and overlaid on top, in hashed/transparent bars is the performance when using text.

A.4 Accuracy over Amount of Training Data

In this experiment, we aim to check how the nomination accuracy of the proposed methods increases as they are allowed to train on more data. Our goal is to verify whether any of the algorithms show signs

[7]The code, along with all the hyperparameters, is available at https://github.com/Anonymised/product-page-dataset.

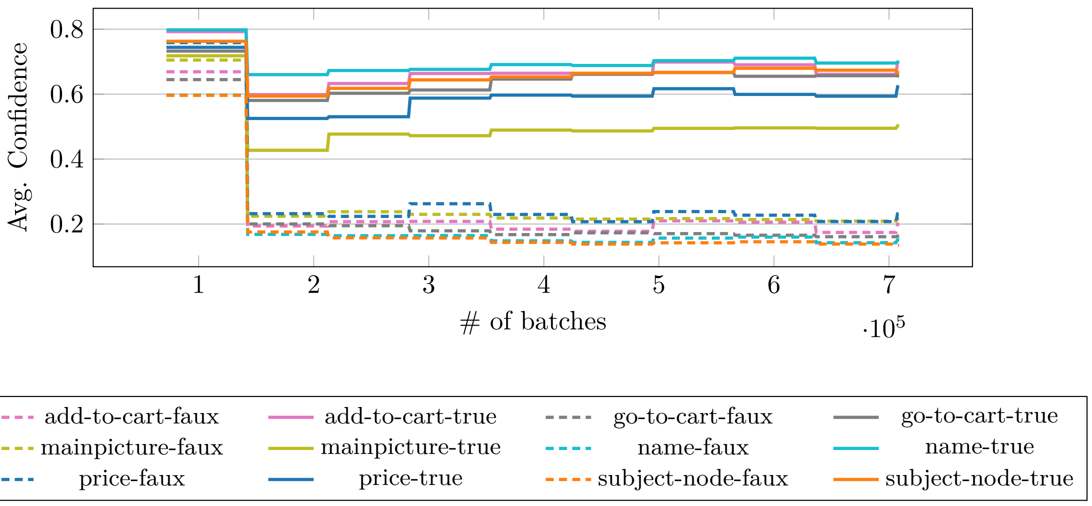


Figure 7: Average confidence assigned by GCN-mean to the true elements are displayed in solid lines, (with suffixes "-TRUE") and the average maximum of the confidence scores of all unlabelled elements on a page are in dashed lines ("-FAUX").

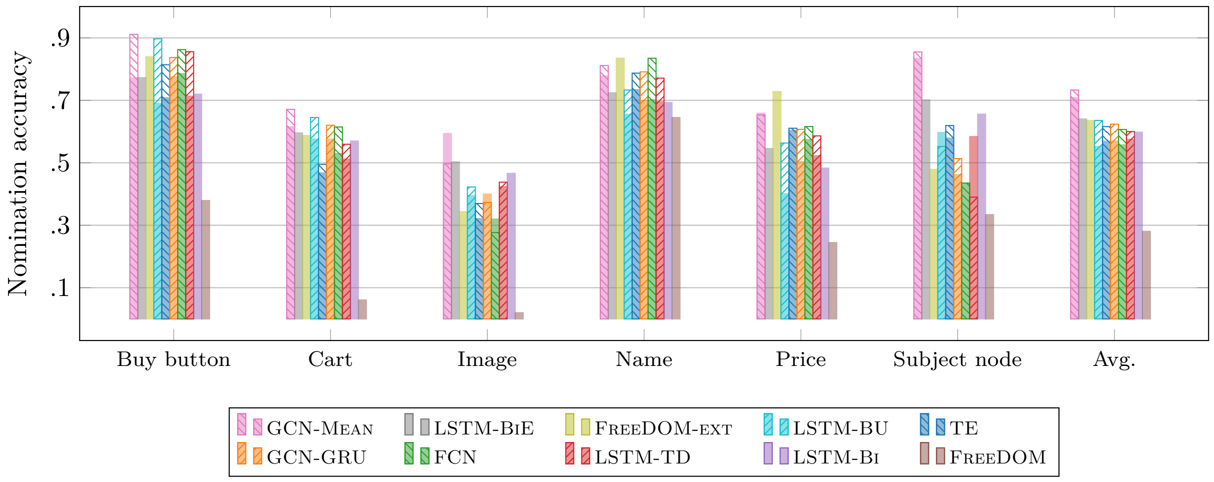


Figure 8: Nomination accuracy with (overlaid dashed bars) and without (solid bars) text included in the local element features.

of performing substantially better as the training set grows. If this were the case, it would suggest the further experiments should be run using a larger training set. We therefore trained the models on 5 subsets from the Klarna Product Page Dataset increasing in size by powers of 2, from 128 to 2048 DOM trees and an additional 6-th dataset containing the $10,000$ webpages in the previous experiment. Each model was trained with fixed hyperparameters, all models use internal representations of size 150, for 50 epochs on every dataset, on only the local style features. The average predictive performance over the 6 labels of each model over the 6 datasets of increasing sizes is displayed in Figure 9. Here, again we see that, among the best performing algorithms, GCN-Mean also exhibits the largest accuracy gain from adding more data. This raises our confidence that convolutional neural networks are worth considering in more detail for web element nomination tasks.

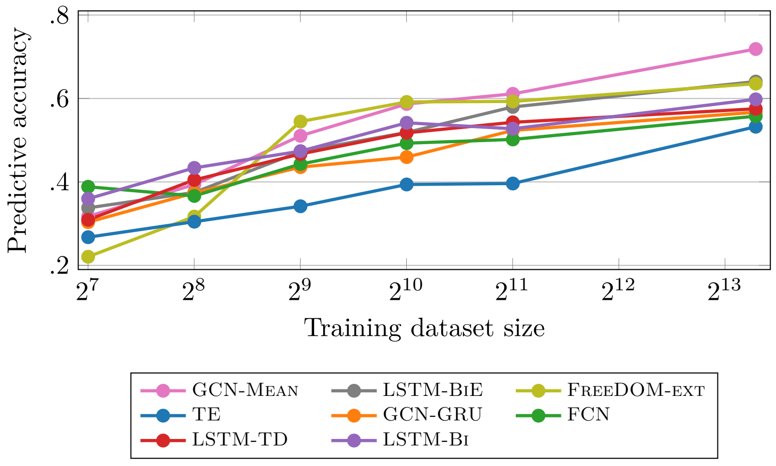


Figure 9: The nomination accuracy (averaged over classes, measured on the validation set) of each algorithm, when trained on the same training sets of increasing size.

A.5 Classification Performance

We also provide additional precision and recall metrics corresponding to the performance of the trained models evaluated in Table 2. Table 4 details the classification performance of the models without text features. When using text features, the results are very similar hence we do not present them here to save space. These metrics show that all models achieve high classification performance, pointing towards them being sufficiently trained on this objective.

A.6 Formulating an Element Nomination Objective

In this section, we discuss the complexity of formulating an objective for element nomination. At first glance, it might appear feasible to design an architecture where the final layer outputs one value per node and class, applying a softmax function across all nodes for each class, and then directly learns to nominate elements using a cross-entropy loss. However, in the following sections, we will outline several challenges and limitations associated with this approach.

To understand why this is not straightforward, assume that we have L class labels and that we for now disregard the unlabeled class. Thus, if we have N nodes on a page, we could use L one-hot vectors of length N to encode which nodes belong to each class on a page.

Table 4: Final classification accuracy of trained models (Precision/Recall, trained without text features)

	buy button	cart button	product image	name	price	subject node	avg.
LSTM-Bi	.91/.95	**.92/.95**	**.89/.94**	.93/.89	.85/.90	.96/.91	.95/.95
LSTM-BiE	**.97/.92**	.95/.89	.92/.85	.92/.91	.90/.86	**.96/.96**	.95/.95
GCN-GRU	.95/.92	.93/.86	.90/.88	.90/.90	.89/.85	.95/.93	.94/.94
FreeDOM	.80/.93	.45/.88	.50/.43	.91/.88	.86/.88	.96/.33	.84/.82
FreeDOM-ext	.95/.95	.92/.88	.89/.90	**.97/.95**	**.96/.94**	.92/.91	**.95/.95**
FCN	.96/.91	.94/.81	.91/.80	.89/.91	.83/.88	.93/.94	.93/.93
LSTM-TD	.94/.93	.93/.86	.90/.83	.92/.91	.90/.85	.94/.90	.94/.94
TE	.91/.94	.90/.94	.88/.91	.92/.90	.84/.93	.95/.91	.95/.95
GCN-Mean	.97/.90	.96/.80	.94/.85	.93/.92	.93/.84	.97/.91	.94/.94

Imagine that we map the hidden representations of the N nodes on the page into an $N \times L$ matrix using a function $f_\theta(\cdot)$ and subsequently apply softmax along the nodes for all L classes. Then we could formulate a cross-entropy loss function as:

$$\sum_{l=1}^{L} \sum_{n=1}^{N} p(x_{n,l}) \log q(x_{n,l}). \tag{2}$$

After incorporating the one-hot encoded labels, this double sum just becomes a sum over L terms, one for each class.

The reason why this objective does not work is that it does not instruct $f_\theta(\cdot)$ how to properly handle unlabeled nodes. When $f_\theta(\cdot)$ maps a labeled node into the L class probabilities, it simply assigns a high amount of mass to the l-th correct class. However, for an unlabeled node, it should not learn to assign any mass to any of the L classes, yet because it is a mapping to these L classes it is forced to distribute its mass among these classes somehow.

A natural suggestion for handling this issue is to incorporate the unlabeled class such that $f_\theta(\cdot)$ maps the node embeddings into an $N \times (L+1)$ matrix. Now it remains to decide how to represent which nodes belong to which class. For the labeled nodes, we keep the L one-hot vectors of length N to encode which nodes belong to each class. However, it is now unclear how to encode the unlabeled nodes. One approach could be to use a vector of $N - L$ ones and L zeros, where $N - L$ corresponds to the number of unlabeled nodes on the page.

The issue with this approach is related to class imbalance. After incorporating the labels into the equation above, we now have $L + (N - 1)$ terms, where L terms incentivize the model to identify the L labeled nodes correctly, while $(N - L)$ terms (where N can be up to $20,000$) incentivize the model to learn to recognize unlabeled nodes correctly. With this very large imbalance, the model might as well predict that everything is unlabeled.

One suggestion to mitigate the class imbalance could be to uniformly weight the terms in the loss which correspond to the unlabeled nodes uniformly, resulting in the following cross-entropy formulation:

$$\sum_{l=1}^{L} \sum_{n=1}^{N} p(x_{n,l}) \log q(x_{n,l}) + \frac{1}{(N-L)} \sum_{n=1}^{N} p(x_{n,(L+1)}) \log q(x_{n,(L+1)}). \tag{3}$$

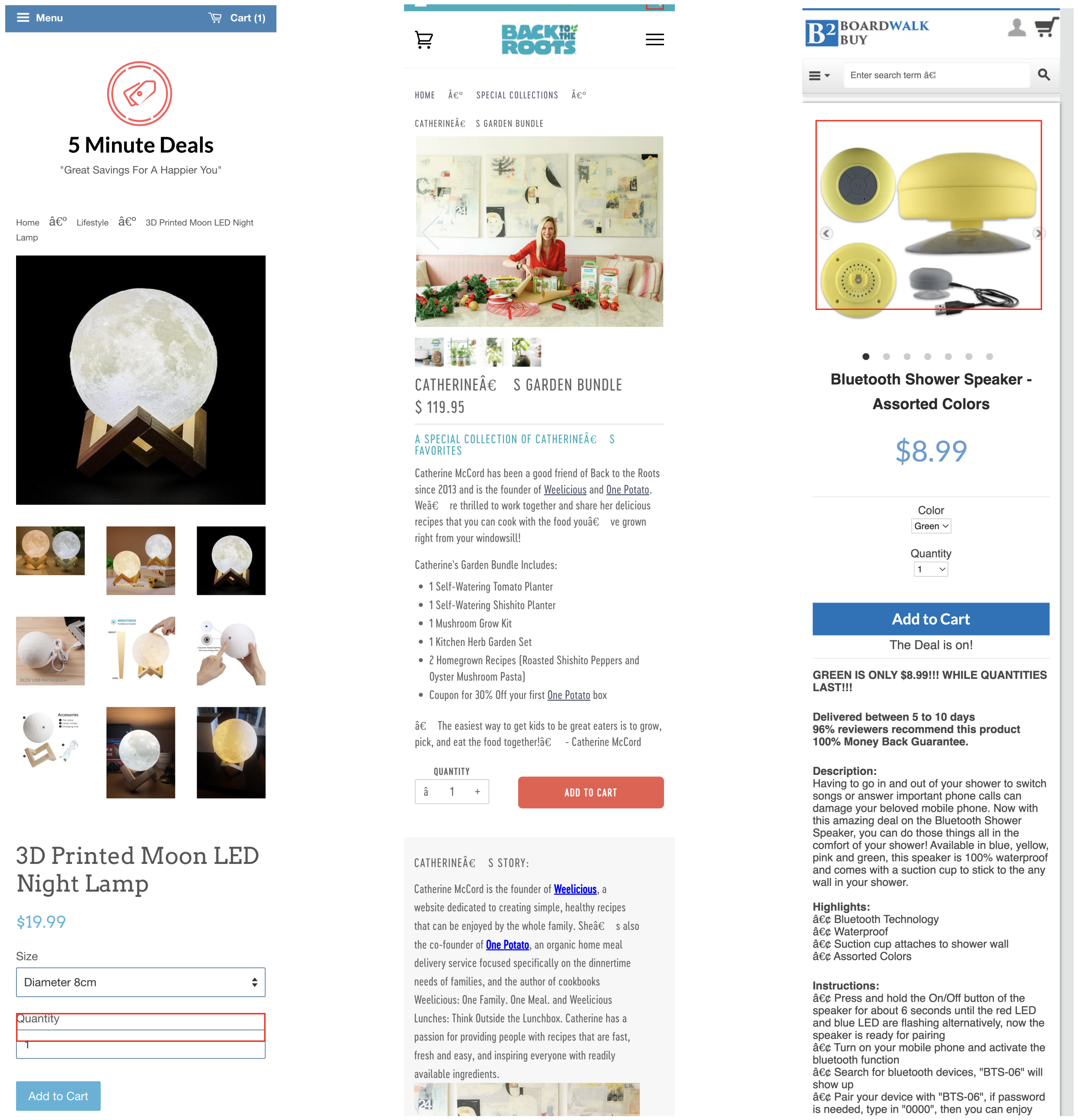
The issue with this approach is that the model is now less incentivized to correctly identify every single unlabeled node. The implication is that when it encounters difficult negative examples, it is less punished for incorrectly assigning more mass to one of the L labeled classes instead of the unlabeled class. Not learning to handle hard negative examples can significantly degrade the final nomination performance, as it just takes a single confusing element to ruin the nomination.

A.7 Model Failures

To gain some intuition about the limitations of our models, we include visualizations of instances where the 20-layer RevGNN algorithm fails, as shown in Figure 10.

A.8 Klarna Product Page Dataset - Additional Statistics

The histograms in Figure 11 show an overview of the complexity that is expected from the pages in our dataset and aim to complement Table 1. The top two plots, displaying the distribution of the size of trees in both heights and the total number of nodes, give a feel for the length of sequences on which the TreeLSTM methods operate and the effect of the number convolutional layers and sizes of the filters. The number of images gauge the amount of noise to be expected when dealing with page screenshots.



Menu Cart (1)

5 Minute Deals

"Great Savings For A Happier You"

Home â€º Lifestyle â€º 3D Printed Moon LED Night Lamp

3D Printed Moon LED Night Lamp

$19.99

Size

Diameter 8cm

Quantity

1

Add to Cart

HOME â€º SPECIAL COLLECTIONS â€º CATHERINEâ€ S GARDEN BUNDLE

CATHERINEâ€ S GARDEN BUNDLE

$ 119.95

A SPECIAL COLLECTION OF CATHERINEâ€ S FAVORITES

Catherine McCord has been a good friend of Back to the Roots since 2013 and is the founder of Weelicious and One Potato. Weâ€ re thrilled to work together and share her delicious recipes that you can cook with the food youâ€ ve grown right from your windowsill!

Catherine's Garden Bundle Includes:

- 1 Self-Watering Tomato Planter
- 1 Self-Watering Shishito Planter
- 1 Mushroom Grow Kit
- 1 Kitchen Herb Garden Set
- 2 Homegrown Recipes (Roasted Shishito Peppers and Oyster Mushroom Pasta)
- Coupon for 30% Off your first One Potato box

â€ The easiest way to get kids to be great eaters is to grow, pick, and eat the food together!â€ - Catherine McCord

QUANTITY

â 1 +

ADD TO CART

CATHERINEâ€ S STORY:

Catherine McCord is the founder of Weelicious, a website dedicated to creating simple, healthy recipes that can be enjoyed by the whole family. Sheâ€ s also the co-founder of One Potato, an organic home meal delivery service focused specifically on the dinnertime needs of families, and the author of cookbooks Weelicious: One Family. One Meal. and Weelicious Lunches: Think Outside the Lunchbox. Catherine has a passion for providing people with recipes that are fast, fresh and easy, and inspiring everyone with readily available ingredients.

B2 BOARDWALK BUY

Enter search term â€¦

Bluetooth Shower Speaker - Assorted Colors

$8.99

Color

Green

Quantity

1

Add to Cart

The Deal is on!

GREEN IS ONLY $8.99!!! WHILE QUANTITIES LAST!!!

Delivered between 5 to 10 days
96% reviewers recommend this product
100% Money Back Guarantee.

Description:
Having to go in and out of your shower to switch songs or answer important phone calls can damage your beloved mobile phone. Now with this amazing deal on the Bluetooth Shower Speaker, you can do those things all in the comfort of your shower! Available in blue, yellow, pink and green, this speaker is 100% waterproof and comes with a suction cup to stick to the any wall in your shower.

Highlights:
â€¢ Bluetooth Technology
â€¢ Waterproof
â€¢ Suction cup attaches to shower wall
â€¢ Assorted Colors

Instructions:
â€¢ Press and hold the On/Off button of the speaker for about 6 seconds until the red LED and blue LED are flashing alternatively, now the speaker is ready for pairing
â€¢ Turn on your mobile phone and activate the bluetooth function
â€¢ Search for bluetooth devices, "BTS-06" will show up
â€¢ Pair your device with "BTS-06", if password is needed, type in "0000", then you can enjoy

Figure 10: Three page screenshots where the model's nominations are inaccurate, with incorrectly identified elements outlined by bounding boxes. In the screenshot on the far left, the model is tasked with identifying the "Buy" button but mistakenly highlights an element located below the product image and price in the center. While the "Buy" button can sometimes be found in this area, it is not accurate in this instance. In the middle image, the model incorrectly identifies a search button in the upper right corner as the "Go to Cart" button, which, although commonly located in this area, is not correct in this context. In the final screenshot on the right, the model inaccurately identifies a div element placed over the product image as the product image itself. These examples illustrate a limitation of relying solely on the DOM tree, as developer design choices are not always consistent or tidy.

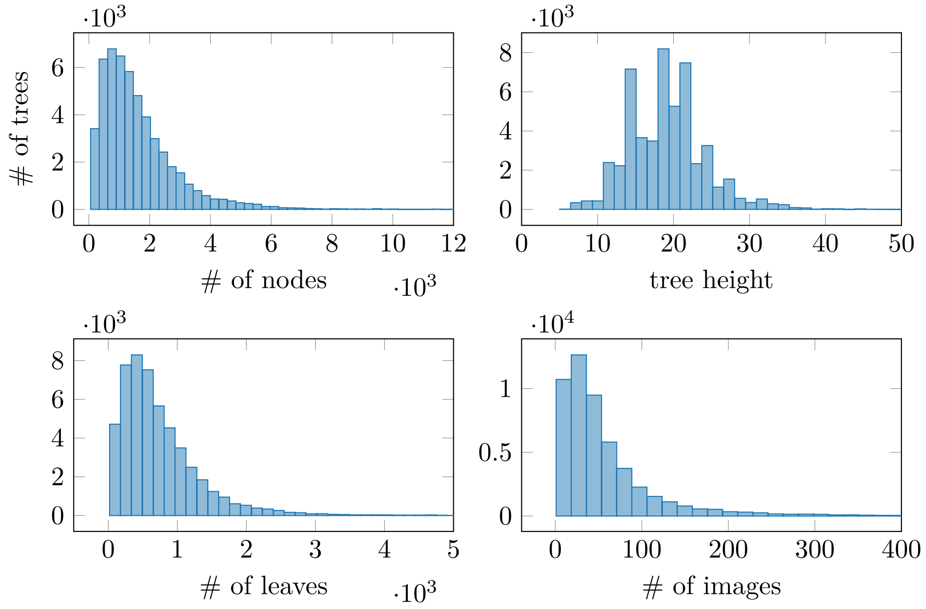


Figure 11: The histogram in the top left corner depicts the number of nodes per tree. To its right, the tree heights are displayed. A tree's height is the maximum possible path length from the root of the tree. In the bottom left corner, we give the number of leaf nodes per webpage, and to its right, we display the number of images (png, jpg, gif) per webpage.