Bridging Semantics for Automated Web Form Testing

Parsa Alian The University of British Columbia Vancouver, Canada palian@ece.ubc.ca

Mobina Shahbandeh The University of British Columbia Vancouver, Canada mobinashb@ece.ubc.ca

ABSTRACT

Automated test generation for web forms has been a longstanding challenge, exacerbated by the intrinsic human-centric design of forms and their complex, device-agnostic structures. We introduce an innovative approach, called FormNexus, for automated web form test generation, which emphasizes deriving semantic insights from individual form elements and relations among them, utilizing textual content, DOM tree structures, and visual proximity. The insights gathered are transformed into a new conceptual graph, the Form Entity Relation Graph (FERG), which offers machine-friendly semantic information extraction. Leveraging LLMs, FormNexus adopts a feedback-driven mechanism for generating and refining input constraints based on real-time form submission responses. The culmination of this approach is a robust set of test cases, each produced by methodically invalidating constraints, ensuring comprehensive testing scenarios for web forms. This work bridges the existing gap in automated web form testing by intertwining the capabilities of LLMs with advanced semantic inference methods. Our evaluation demonstrates that FormNexus combined with GPT-4 achieves 89% coverage in form submission states. This outcome significantly outstrips the performance of the best baseline model by a margin of 25%.

1 INTRODUCTION

In the contemporary digital era, web applications play a crucial role in our daily interactions. These modern applications have become increasingly sophisticated, allowing users to engage in intricate ways. A vital part of the interaction happens through forms. They serve as essential tools for collecting dynamic user data and establishing effective communication between users and software applications. Given their significant role, it is imperative to rigorously test the functionality of these web forms to ensure accuracy and reliability.

While there have been advancements in web testing methodologies [9, 12, 14, 49], the realm of form test generation remains sparsely explored [39]. Generating input values and test cases for forms introduces a distinct set of challenges. Since forms are tailored for human interaction, generating suitable values necessitates a grasp of the *context* of each input field: understanding the semantics of fields, as well as how they relate to one another. In the context Noor Nashid The University of British Columbia Vancouver, Canada nashid@ece.ubc.ca

Ali Mesbah The University of British Columbia Vancouver, Canada amesbah@ece.ubc.ca

of the black box test generation for web forms in particular [18], understanding the Document Object Model (DOM) introduces another layer of intricacy, which can at times overshadow the form's inherent semantics. The flexibility in coding that allows for visually identical displays adds a layer of complexity to the web form's architecture. Furthermore, a push for web applications to be deviceagnostic impacts the design of HTML structures, making it even more elusive. These complexities can pose significant hurdles for the automated testing of web forms.

Given the imperative to comprehend form semantics for automated test generation, leveraging Natural Language Processing (NLP) techniques for form input generation emerges as a promising avenue. The spectrum of potential methodologies has broadened notably with the recent introduction of Large Language Models (LLMs) such as GPT-4 [37] and Llama-2 [45]. The adeptness of LLMs in emulating human-like language processing and generation paves the way for a new approach to this endeavor. Recently, studies have leveraged LLMs for a wide array of tasks, such as unit test generation [25, 28, 34, 40, 41, 48] and mobile app formfilling [32]. The advent of these techniques presents an exciting frontier in addressing the complexities of automated web form test generation.

In this paper, we introduce **FORMNEXUS**, a novel LLM-agnostic technique designed explicitly for the automated generation of web form tests. At its core, this method grapples with the intricacies inherent in understanding the context of input fields. We do this by transforming the form's DOM layout into a more organized structure, called Form Entity Relation Graph (FERG), where the semantics and relationships of form elements become more clear and better suited for machine interpretation. To make this transformation possible, we analyze each node's characteristics, including its textual content and position in the DOM hierarchy. Based on these factors, we determine similarities between various HTML nodes and identify potential relationships between different nodes, which in turn provides insights into the semantics of individual inputs and the connections that might exist between them.

After establishing the semantic linkages within the form, we adopt a feedback-driven methodology that leverages these connections in conjunction with LLMs to formulate test cases for the form. The procedure begins by deducing preliminary constraints rooted in semantic associations, followed by generating input values in accordance with these constraints. FORMNEXUS then verifies, and if needed modifies, the inferred constraints, generates new input values, and submits the form under these modified constraints. Our

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goal is to corroborate the constraints using the feedback obtained after submission. Once the constraints are validated, FORMNEXUS converts them into a comprehensive set of test cases. These cases serve as a valuable vehicle for checking and deciphering the form's runtime functionality.

To evaluate FORMNEXUS, we employ a diverse selection of realworld and open-source applications. We utilize LLAMA 2 and GPT-4 as the LLM underpinning FORMNEXUS. Our results show that FORM-NEXUS instantiated with GPT-4 delivers the best results, achieving a state coverage of **89**% marking a significant **25**% improvement over the next best performer baseline, GPT-4 alone. Additionally, successful form submission test cases are equivalent to the form-filling task, where FORMNEXUS with GPT-4 demonstrates **83**% success rate in successfully submitting and passing the forms, outperforming all other baselines by at least **27**%. Our evaluation also scrutinizes the individual modules of FORMNEXUS, revealing the contributions of the different components, the inference of semantic relations via FERG, and our feedback loop approach toward the overall effectiveness of our technique.

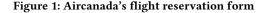
This work makes the following contributions:

- A novel technique for discerning the semantics and intricate interrelationships of web form components.
- An approach for inferring input field constraints and values using a combination of semantics captured in a Form Entity Relation Graph (FERG) and an LLM.
- A method for generating a test suite covering both successful and failing form submission states.
- A new dataset containing a collection of web forms, each annotated with input values and accompanying submission states, enabling a comprehensive evaluation of the coverage of form tests.

2 MOTIVATING EXAMPLE

In our study, we use the Air Canada's [1] flight reservation web form as a motivating example, illustrated in Figure 1.

It is not possible to search for flights which have both an origin and a destination in the United States.	1
● Round-trip One-way O Multi-city/Stopover	
Book with points AEROPLAN 🛞	
From	
Please select a valid point of origin for this trip.	- ↑↓
То	
Departure Return	
Passenger(s) 1 Adult	•
Search flights	



Prior to the deployment of such forms, developers must conduct comprehensive testing to ensure the form's appropriate responsiveness to both valid and invalid inputs. The effectiveness of the test cases can be evaluated by examining the extent of coverage of *Form Submission States*.

Definition 1 (Form Submission State (FSS)). A *Form Submission State* is an ordered tuple S = (I, C), wherein *I* represents the set of inputs subjected to testing during the form submission, and *C* constitutes the list of modifications to the source of the page post form submission. In other words, each submission state maps to an execution path for the function that operates behind the web form.

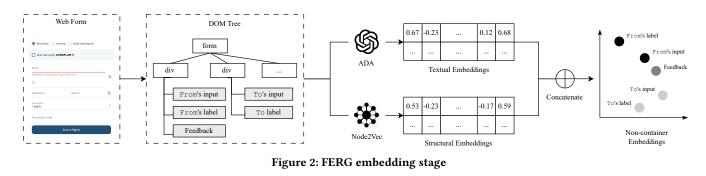
While the interface of this form appears straightforward, it encompasses a variety of scenarios that could potentially lead to errors, each necessitating thorough testing. First of all, each input field in a form is designed to accept values of a specific type and pattern. For example, date fields, such as Departure and Arrival, cannot accept random strings; they require inputs that adhere to a predefined date format. Similarly, other input fields may be restricted to specific formats, such as email addresses, telephone numbers, or other custom patterns. Beyond these standard validations, forms may also involve more intricate scenarios that warrant further examination. Consider the following examples from Figure 1:

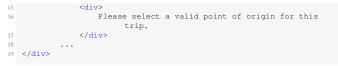
- Geographic constraints play a crucial role in the travel planning mechanism. Specifically, the points of departure and arrival (From and To) must differ, as it is logically inconsistent to embark on a journey that begins and ends at the same location. For example, while a trip from Toronto to New York is feasible, a journey from Toronto to Toronto is not.
- The order of temporal events is equally vital. Travel dates must be arranged in chronological order, with the Return date necessarily occurring after the Departure date. The system should also be capable of detecting and signaling any discrepancies, such as dates set in the past or unreasonably far in the future. For instance, a journey commencing on Dec 25th and concluding on Dec 31st is valid, but not vice versa.

Forms similar to the flight reservation interface illustrated in Figure 1 are ubiquitously encountered and effortlessly navigated by human operators, who inherently understand the logical restrictions these forms entail. In contrast, computational systems encounter significant obstacles in generating valid and invalid inputs for such forms. An initial challenge lies in the precise identification of the intended functions of input fields within web forms. This challenge becomes evident when examining the simplified HTML structure of the From field, as detailed in Listing 1.

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Listing 1: Air Canada's From Input Field

If key attributes such as id, for, and aria-label are absent from these elements, discerning the purpose of an <input> element in such HTML code becomes virtually impossible, a scenario not uncommon in many web applications. Identifying labels for input fields can be problematic, especially when they are not directly associated through the labels' for attributes. Furthermore, linking other textual elements, such as feedback or hint texts, to inputs is often more complex due to the lack of explicit connections.

Understanding the relationships between input elements and their associated textual features is a complex task that extends beyond straightforward hierarchical heuristics. The inherent flexibility in HTML coding practices, which allows for numerous structural variants to achieve similar visual outcomes, significantly limits the effectiveness of these heuristics. Developers often insert <div> or elements to implement specific styles or functionalities, adding a layer of structural complexity that is visually subtle but significant for computational interpretation.

Another method to discern relationships between form elements is by examining their textual features. However, there are instances where elements may share a semantic relationship but lack direct associations. For example, the terms From and Departure in a form can be considered semantically related, yet they do not have explicit constraints linking them during the form completion process.

After identifying the textual context of an element, computational systems face the significant challenge of interpreting the semantics of labels and other contextual texts to accurately generate values for input fields. This task necessitates a sophisticated level of NLP capability. Furthermore, the specific context of the application in question is critical, as identical textual cues can carry different meanings in various applications. For instance, in a travelrelated form, the term From might signify the point of departure or the departure date. In contrast, in a personal information form, From could pertain to the user's nationality.

The final challenge encountered by computational systems involves comprehending the interrelationships among various input fields. Such interconnections often lead to specific constraints, exemplified by the geographical dependencies within location fields or the chronological ordering required in date fields in Figure 1. To encapsulate the entirety of information necessary for generating values for an input field, we define the concept of *Input Field Context* as follows:

Definition 2 (Input Field Context). The term *Input Field Context* refers to any pertinent information that assists in clarifying the requirements and limitations of a given input. This context may manifest as textual annotations associated with the input field such as labels or hint texts, or it might be derived from other input fields that influence and define the constraints of the focal input.

The concept of *Input Field Context* encompasses a comprehensive set of requirements pertaining to individual input fields within a form. These requirements may include the specification of data types that are deemed acceptable for each field, as well as the delineation of relationships between various fields. Such a framework allows for the categorization of different scenarios as either conforming to or deviating from these established requirements, thereby providing a structured basis for rigorous testing.

3 APPROACH

In this work, we introduce FORMNEXUS, a novel approach for web form test generation. The main focus of our method is to understand the context of each form element. Then, by harnessing the capabilities of LLMs and employing a feedback-driven approach, we decipher the constraints tied to input fields, which aids in value generation. These identified constraints then form the foundation upon which we craft test cases for the web form.

3.1 Input Context Construction

To tackle the complexities associated with comprehending the context of input fields, as discussed in section 2, we introduce a novel approach that converts the form's DOM tree into a graph structure, termed the Form Entity Relation Graph (FERG). The goal of this graph is two-fold: first, it enhances the contextual information of each individual input field, second, it captures information pertaining to how relevant form entities are to each other and provides a quantitative score of the relevance.

As discussed in section 2, relying solely on either textual or structural attributes of a form's elements may not adequately reveal the interrelationships among them. We hypothesize that a combination of these attributes should reveal a clearer sense of connectivity between elements, in contrast with relying on them solely. To achieve this, we employ embedding techniques to combine the individual

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features of the elements, thus overcoming their separate limitations. Subsequently, these combined embeddings are utilized to elucidate potential relationships among the elements. This is achieved by constructing a graph, FERG, which represents the interconnected structure of the elements.

3.1.1 **Creating Embedding Space**. In the construction of the FERG, the initial step involves establishing an embedding space for the elements within the form, as delineated in Figure 2. To encapsulate the connections in the form, we start by generating textual and structural embeddings for non-container elements. In the realm of web forms, non-container elements are defined as those either directly encompassing textual content or functioning as input elements, and these are the elements that users directly interact with. For the generation of text embeddings, which involve the transformation of sentences into embedding vectors, we utilize ADA [35] embeddings. To elucidate the structural relationships among elements, we apply the node2vec methodology [19] on the DOM tree. This approach results in a distinct embedding vector for each node within the DOM tree.

We iterate over the non-container nodes from the DOM tree and calculate the textual and structural embeddings for these nodes. We concatenate the embeddings to form an embedding space, in which we expect to find the similarity of different nodes. For example, since the From *label* is structurally close to the From *input* field, and also the text in the label (From) is similar to the aria-label of the input From as illustrated in Listing 1, we expect these two elements to fall close to each other in the embedding space. We can then use similarity metrics such as cosine similarity to measure the closeness of the nodes.

3.1.2 **Local Textual Context**. The first type of context that we aim to clarify is the local textual context. This context commonly consists of any piece of text that might provide clarifications for the input field, such as labels, hint texts, or any relevant feedback for the input field. These relationships are key to deciphering the nature of an input field.

We can observe in Figure 1 that textual elements that are related to each input field are positioned close to their related input field. For instance, the From input field is closely flanked by two related elements: its corresponding label From and the feedback text (Please select a valid point of origin for this trip), both sharing visual boundaries with the input field. This phenomenon is typically true in forms since proximity also aids human operators in associating the textual information with the input field. So in this phase of our methodology, we start connecting the elements that share visual boundaries.

We iterate over input fields and compute the cosine similarities with their adjacent textual elements. These calculations are integrated into a graph G = (V, E, W), where V represents the graph's nodes, encompassing the non-container nodes in the form. E denotes the edges connecting visually adjacent elements, and Wsignifies the weight of these edges. The weight is determined by the cosine similarity between the embedding vectors of the elements, which quantifies the extent of contextual dependency between two connected elements. A sample of the formed graph can be seen in Figure 3.

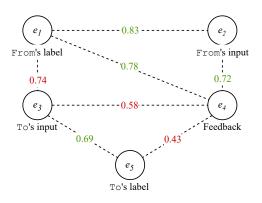


Figure 3: Relating the local textual context

It is worth noting that being neighbors does not always translate to being related. In Figure 1, the feedback text also borders the To input field, yet it holds no relevance to it. Therefore, the formation of the initial graph is followed by a pruning process. In this context, we categorize entities within the form into two types: main and auxiliary. Input fields are treated as main entities or *first-class citizens* in form contexts; they are capable of existing without any other elements, such as labels, with their function potentially indicated via attributes such as placeholder or value. Conversely, auxiliary elements, such as labels or hint texts, inherently depend on the existence of an input field for their relevance. A form composed exclusively of labels or hint texts would lack functional meaning without connection to input fields.

This conceptual framework informs our edge pruning strategy within the graph *G*. We begin by examining the auxiliary (noninput) nodes in the graph. For each of these nodes, we inspect the edges connected to it. If an auxiliary node is linked to multiple input fields, we retain only the edge with the highest cosine similarity score. For instance, in Figure 3, From's label and feedback are connected to both From and To input fields. However, since the similarity score of their connection is stronger with From's input field, we only keep those edges.

As for text-to-text edges, we apply a statistical method for their retention. We compile the scores of all such edges and filter out those less than the threshold of $\mu + \lambda.\sigma$, where μ represents the mean score, σ the standard deviation, and λ is a predetermined factor set at $\frac{1}{2}$. Again, in Figure 3, the feedback is connected to both From and To labels, although the connection to label To is not statistically significant for us to keep in the graph. After applying the filtering process, edges removed from the graph are indicated in red in Figure 3, while the remaining edges are shown in green.

3.1.3 **Relevant Input Context**. Having established the textual context for each input field, the subsequent phase of our method identifies relevant inputs that are interrelated. Figure 1 demonstrates that input fields with relationships, such as From and To or Departure and Arrival, not only share a similar textual context but also are often in close structural proximity. This design is intuitive for human interpretation. The relationship between elements is typically indicated by semantically related labels and their spatial

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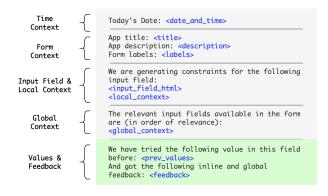


Figure 4: Constraint prompt structure

closeness, as the significant distance between elements generally diminishes their perceived relevance.

In light of this observation, we utilize the embeddings previously computed to gauge the degree of connectedness between groups of input fields. Employing the same embedding is advantageous for this task, as it encompasses both textual similarity and structural proximity. We define the relationship score between two input fields (InputFieldSim) as the maximum of the input-to-input and label-to-label similarity scores as follows:

```
InputFieldSim = \max\{sim(label_1, label_2), sim(input_1, input_2)\}
```

In instances where input fields lack associated labels, we adapt the methodology by omitting the label terms from the calculation.

It is important to recognize that the relationships discerned between input groups are not inherently obligatory; lower score relations do not necessarily imply a meaningful connection. To effectively identify and exclude less relevant relationships, we employ the same statistical approach previously applied to text-to-text edges, as outlined in subsubsection 3.1.2.

3.2 Constraint Generation and Validation

Our objective now is to use the information in FERG to infer a series of constraints that align with the attributes and relationships of the input fields within the form. In an iterative process, we query the previously constructed FERG to extract relevant elements for each input field. We construct prompts based on the retrieved information and subsequently prompt the LLM for constraint and value generation.

3.2.1 Initial Generation Phase. Following the connection of input fields to their corresponding elements within the form, we can make educated guesses regarding the specific constraints associated with each field. For instance, at this stage, we possess knowledge of the type requirement imposed upon the From input field, derived from its underlying HTML code (Listing 1), we have inferred the surrounding textual context including its associated label, and we have established a relationship between the From and To input fields. Leveraging this information, humans are capable of inferring a significant number of constraints (e.g., the field should be alphabetical, not equal to the To field, etc.). If the specific application context for which the form is intended is known, we can infer virtually all of the constraints for the From field, as outlined in section 2.

Leveraging the vast datasets on which LLMs are trained, we anticipate their ability to perform similar inferential tasks as humans. Therefore, following the construction of FERG, our subsequent step involves utilizing the relationships and information it encodes to infer an initial set of constraints for the form's input fields. To achieve this, we employ an LLM, tasked with selecting a series of constraints from a pre-defined list of constraint templates, as outlined in Table 1.

Table 1: Constraint Templates

Signature	Definition
toBeEqual(value)	The input field value is exactly equal to the given value.
<pre>toHaveLengthCondition(condition, value) toBeAlphabetical()</pre>	The length of the input field value matches the given condition. The input field should be alphabetical.
toContainWhiteSpace()	The input field should contain whitespace.

While the generated constraints derived from these templates are readily evaluable functions, it is crucial to acknowledge that certain inherent complexities within web applications cannot be effectively captured using such functions. A pertinent illustration can be observed in the Air Canada form depicted in Figure 1, where the user encounters the following error message:

"It is not possible to search for flights which have both an origin and a destination in the United States."

In recognition of this limitation and to accurately represent such intricate logical constraints prevalent in forms, we have introduced a novel constraint type, termed freeTextConstraint. This type specifically caters to the capture and articulation of scenarios that transcend the capabilities of conventional constraint types.

Our approach to prompting the LLM begins by focusing on each input field. We employ a structured prompt, the details of which are outlined in Figure 4. This prompt includes the following information:

- Time Context: This detail facilitates constraint generation for date fields by enabling the LLM to compare them with the current date.
- (2) Form Context: To provide general context about the form, we incorporate its title, description, and labels from the form's metadata. This information informs the LLM about the type and purpose of the application, thereby facilitating more accurate and relevant constraint generation.
- (3) Input Field and Local Context: We provide the HTML of the target input field as context for the LLM. Additionally, we include local textual context extracted from FERG (subsubsection 3.1.2 to hint at the input field's intended purpose within the form structure.
- (4) Global Context: We consider elements that have a global association with the input field (subsubsection 3.1.3) and incorporate them into the prompt. These inferred relationships assist the



Figure 5: Value prompt structure

LLM in understanding the inter-variable constraints of the input field.

For each input field, the LLM is provided with these pieces of information, and it is asked to select a set of constraints from constraint templates in Table 1. Given the extensive training of the LLM on a diverse data corpus, we anticipate its ability to grasp the semantics embedded in each input field, and leverage form and FERG's contextual information as guidance. As a result, we expect the LLM to generate a set of constraints closely mirroring the real-world constraints associated with these fields. An example of the LLM's response is demonstrated in Listing 2, showcasing the constraints generated for the From field in the Air Canada form depicted in Figure 1.

```
expect(field('From'))
.toBeTruthy()
.toBeAlphabetical()
.toHaveLengthCondition('>', 2)
.not.toBeEqual('To')
```

Listing 2: From field's generated constraints

The presented example illustrates the generation of specific constraints (lines 2-4), which are literal, and extrapolated from localized data such as labels. This field is expected to satisfy several conditions, namely, it should (1) not be empty (line 2), (2) adhere to a specified minimum length (line 3), and (3) contain exclusively alphabetical characters (line 4). Additionally, certain constraints (line 5) depend on values drawn from different fields; for instance, (4) the From and To fields are expected to be distinct. These four constraints concisely mirror the anticipated requirements for the values of the To field.

The constraints generated by the LLM form a crucial basis for approximating the underlying logic inherent to the input fields, thereby facilitating the generation of appropriate values for the form. This process of value generation is executed by directing the LLM to produce values that comply with the deduced constraints. The specific structure of the prompt used for guiding the LLM in value generation is detailed in Figure 5. This prompt includes:

- (1) Form Context, Input Field, and Local Context: These sections are identical to the constraint prompt, and are included for the LLM to grasp the overall context of the form. The Time Context is omitted, as we expect the date and time requirements to reflect in the generated constraints.
- (2) Constraints and Values: These are the generated constraints resulting from prompting LLM previously. Since we generate

values one by one, we include the generated values for relevant fields in the constraints. As an example, while generating value for From field, we mention input field should not be equal to 'Toronto', following the constraint on line 5 of Listing 2.

With the contextual information in this prompt, the LLM can effectively generate a variety of values that may meet the requirements of the form.

3.2.2 **Feedback Loop and Constraint Updating**. Upon completion of the previous step, we obtain a series of constraints and values based on the context of the form. However, at this point, we have not interacted with the form yet, and the adequacy of these values for the form is still undetermined. Therefore, the next step is to populate the form with these generated values and subsequently submit it, thereby triggering a response or *feedback* from the form.

After the submission of the form, several scenarios can unfold. The user might either remain on the initial page or be redirected to a new page. In each of these scenarios, textual indicators may appear, signaling either the success or failure of the form submission. In general, we can define the success or failure of the submission as follows:

Definition 3. A *Failure* in submission is identified by the reception of error feedback from the web application. In contrast, a *Successful* submission is denoted by the absence of such failure feedback and the transition to the intended outcome of the form.

For instance, in the case of Air Canada's flight reservation form, a successful submission would navigate to a page displaying available flight options, while a failed submission would typically generate error messages.

Given the complexity inherent in identifying the state of the page post-submission, we employ a heuristic-based approach to discern the form's status. This involves calculating the differential (*diff*) of the DOM tree before and after the form's submission. Subsequently, we refine these differences by filtering them through specific keywords commonly associated with feedback messages, such as not valid, required, denied, and similar terms. The elements that emerge after this filtration process are then regarded as the feedback resulting from the form submission. It is important to underscore that this method can be effective in identifying feedback irrespective of whether the submission leads to a page redirection or remains on the same page since it searches for the failure keywords on the page.

After submission, the FERG creation algorithm can be redeployed to update the FERG. Using this algorithm, we can connect the inline feedback that is in the form to their respective input field, using the local textual context connection described in subsubsection 3.1.2. However, there might be some pieces of feedback text that the algorithm is not able to connect to input fields, because it is not in the proximity of an input field, or because of the page redirect, which results in the form not being available. In both of these cases, we are dealing with *global* feedback, which is feedback that is applied to multiple fields or all of the input fields in the form. For instance, the error present at the top of Figure 1 (flight being in the United States), is not attached to any specific input. To refine the constraints and ensure their accurate representation of the form's requirements, we initiate another prompting process with the LLM, as delineated in Figure 4. This process involves generating a new set of constraints, considering the feedback received from the previously submitted values. The feedback part can be viewed at the end of the constraint prompt in Figure 4. In this iteration, the previously submitted values and post-submission feedback are incorporated into the prompt, allowing the model to align its responses more closely with the received feedback. This includes integrating inline feedback for each element, and in instances of global feedback, incorporating it into the prompts for all elements.

This refined approach enables the LLM to adjust and fine-tune the constraints in response to the provided feedback, thereby facilitating the generation of new values that comply with these updated constraints. The form is subsequently resubmitted with these new values, and this iterative cycle is repeated until a successful form submission is achieved. At this juncture, the algorithm concludes its operation. Successfully reaching this stage allows us to assert with considerable confidence that the derived constraints accurately mirror the actual requirements stipulated by the form.

3.2.3 **Constraint Validation**. After finishing the previous step, we are left with a set of constraints that can pass the form. While these constraints may have facilitated successful form submissions, they could be unnecessarily restrictive. Take, for instance, the constraints in Listing 3, particularly toHaveLengthCondition('>', 2). This appears to be a reasonable constraint for the field, however, the developers might not have applied any length restrictions to this particular field. Even though any values with lengths exceeding 2 will pass the form validation, this constraint might not accurately reflect the intended logic for the form.

To validate these constraints, we leverage an iterative process where we analyze the deduced constraints for each field. During each iteration, we negate one constraint at a time while preserving all other constraints and generating corresponding values for evaluation to make sure that the constraint is a valid one for the input field. For instance, considering the To field and the length constraint, the corresponding validation constraint would be .not.to-HaveLengthCondition('>', 2).

expect(field('bkmgFlights_origin_trip_1'))
.not.toHaveLengthCondition('>', 2)

Listing 3: Air Canada's To Field Constraint Negation

We employ these revised constraints to generate a value for the field and proceed to submit the form. The form submission can yield two potential outcomes:

- **Success**: This indicates that the initial constraint was ineffective and not considered by the developers. Nonetheless, as this constraint was derived from the semantic interpretation of the input field and was expected to hold, we recorded this discrepancy in a database. This acts as a notification to the developers about the discrepancy between our expectations based on semantic interpretation and the actual logic of the input field. Therefore, we keep this attempt as a test in the test generation phase.
- Failure: A feedback indicating a failure validates that the initial constraint was correctly inferred since its negation causes

failure. We preserve the values used in the form along with the feedback (both inline and global) for generating assertions in the subsequent test generation phase.

After iterating through these steps for every input field and each associated constraint, we accumulate a database comprising discrepancies, submission success, and submission errors.

3.3 Test Generation

The overarching objective of our test generation is to cover a comprehensive range of form submission states, inclusive of both successful and failed form submissions. Each test case examines a submission state of the form-under-test (See Definition 1).

Throughout the prior stages, we have generated and validated anticipated constraints for each input field. We expect these constraints to correspond to a potential execution path within the form's functionality. By submitting values that either adhere to or violate each constraint, we are effectively verifying the presence of the associated execution paths within the form's logic. Simultaneously, we systematically record the input values used and the resulting outcomes of each form submission in a database for future reference and analysis.

According to this scheme, each set of values and submission outcome that we encountered in the previous phases can be transformed into a test case. These tests essentially function as endto-end tests for the form under examination, ensuring its correct operation under varying input conditions. From the local relation edges, we obtain single-variable test cases, and we generate test cases for the combination of different input fields using the relations that we inferred during global relation creation. Each generated test case performs the following actions: (1) navigate to the page containing the form, (2) populate the form fields with the inferred values, (3) submit the form, and (4) assert that the submission state expected is present on the page.

3.4 Implementation

FORMNEXUS is developed in Python and supports the integration of either the GPT-4 [37] or the LLAMA 2 [45] model. We opted for GPT-4 due to its established performance as one of the most advanced LLMs available, while LLAMA 2 was chosen for its demonstrated capabilities as a top-performing open-source LLM across various benchmarks. For textual embedding generation, we utilized the ADA architecture [35], and a standard implementation of node2vec [19] to capture the underlying graph structure. The definition of our constraint templates drew inspiration from the Jest library [4], a testing framework equipped with a comprehensive set of built-in assertions for evaluating variables under diverse conditions. By adapting these assertions to our specific requirements, we arrived at a final set of 14 constraint types. Notably, the test cases generated by FORMNEXUS leverage the Selenium framework [5] for robust execution.

4 EVALUATION

We have framed the following research questions to measure the effectiveness of FORMNEXUS:

• RQ1: How effective is FORMNEXUS in generating tests for forms?

Table 2: Dat	taset Categories
	1

Category	Form Count	Input Count
Travel	8	31
Query	13	17
Registration	4	24
Data Entry	5	30
Total	30	102

- RQ2: How does FORMNEXUS compare to other techniques?
- **RQ3**: What is the contribution of FORMNEXUS's components towards the end results?

For running our experiments, we set the temperature parameter of the LLMs to 0 to produce the same response every time.

4.1 Dataset

Given that there exists no dataset that contains information about form values and the associated submission states, we curated and annotated a list of web forms. Drawing from the Mind2Web dataset [16], which comprises a wide array of popular websites in the US across various domains, we aimed to construct a diverse dataset. Additionally, to address tasks that are infeasible in real-world applications using automated tools, such as user creation, we integrated opensource applications into our dataset. Our selection criteria for forms included: (1) representation across a range of web application domains; (2) diversity in form types and categories; (3) presence of input value validation, crucial for evaluating baselines and our technique's efficacy in exploring these validation scenarios; and (4) forms that do not require user authentication, making them more accessible for real-world application analysis.

Our emphasis was primarily on free-form input fields such as text, number, or date inputs, necessitating value generation, rather than selection-based inputs, i.e., checkboxes or dropdowns.

Table 2 presents the range of subjects covered in our study, along with the respective counts of forms and input fields in each category. Our methodology was assessed on a total of **30** web forms, spanning **4** distinct categories of functionality. These forms incorporate a cumulative total of **102** input fields, with individual forms containing between 1 to 14 inputs, averaging at 3.4 inputs per form. Each form implements some level of validation, varying in complexity, thereby contributing to the diversity of our test dataset. Out of 30, 6 of the forms were from open-source applications containing 37 of the input fields, while the rest were from real-world applications.

Ground Truth. To evaluate the effectiveness of FORMNEXUS in testing forms, we evaluate the number of *Form Submission States* (*FSS*) (Definition 1) it can cover; this includes covering both successful and unsuccessful states of form submission (Definition 3). To this end, we need a ground truth for the number of states that a form can have after submission. Finding this number can be a difficult task, with or without having access to the source code of the application. To create a ground truth, the authors tried various inputs for the subjects, capturing both the input values and the corresponding form feedback as essential data points in our dataset. This process involved the following steps:

- (1) **Initiating with Passing Values**: Each author begins by exploring an initial set of passing values, ensuring the submission is successful.
- (2) Incremental Input Variations: Each author systematically modifies one input value at a time while keeping the other inputs fixed. This approach allows us to explore different scenarios and gather various feedback (i.e., FSSs) from the form for each specific input variation. After finishing single variable modifications, we also check modifying possible meaningful combinations of inputs to discover more FSSs.
- (3) Aggregation: After each author independently finishes the discovery process, we aggregate the discovered states. Discrepancies are discussed and resolved in this step as well.

Following this methodical approach, we comprehensively cover a wide range of input combinations, obtaining valuable insights into how the forms respond to various user inputs.

4.2 Baselines

As previously stated, the field of generating test cases for web forms is sparsely explored. We considered employing Santiago et al. [39] as a baseline for our comparison. However, it was excluded from our comparison due to the unavailability of their replication package and the absence of a detailed description of their approach.

To assess our method's efficacy, we compared it with various alternative strategies. Our first approach involves a *static* module that tests pre-defined values, chosen to identify potential errors based on the input field's type attribute. For example, in numeric fields, this module inputs extremes like very large or small numbers, including zero. Additionally, we utilize Crawljax [33], a web crawler equipped with a random value generation for form inputs, to generate 20 values for each input field in our subjects. We use these values to test the forms.

An alternative approach for test case generation is directly employing the LLM. In this approach, we designed modules to prompt GPT-4 and LLAMA 2 with the forms' HTML, directing these models to generate both successful and erroneous test inputs for each form. This approach bypasses the additional techniques incorporated in FORMNEXUS.

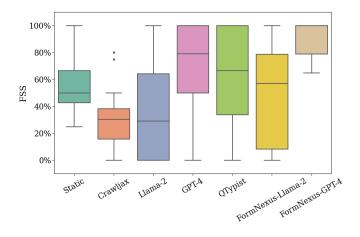
We also adopt a method akin to QTYPIST [32] for generating a variety of test values. A direct application of QTYPIST was not feasible as it was not intended for testing, and the model used, the Curie version of GPT-3 [13], is no longer available for finetuning. Additionally, the specific dataset used for fine-tuning was not disclosed in their repository. Therefore, we utilized GPT-4 [37], applying linguistic patterns similar to those described in QTYPIST, and instructed the model to generate both passing and failing values for the form. This can give QTYPIST an advantage since GPT-4 is likely more powerful than their fine-tuned model.¹

4.3 RQ1: Effectiveness

Our primary objective is to cover as many states behind forms as possible. Thus, we measure effectiveness as a percentage of covered FSSs.

¹We also considered Auto-GPT [2], but it was unable to generate form input values.

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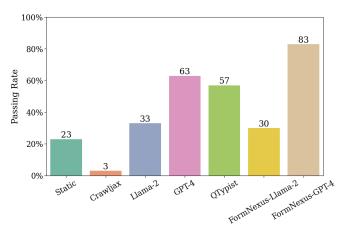


Figure 6: Box plots of FSS Coverage

Figure 7: Passing Rates

Figure 6 illustrates the distribution of FSS coverage for different methods. Tests generated by FORMNEXUS-GPT-4 and FORM-NEXUS-LLAMA 2 successfully cover **51%** and **89%** of the known FSSs respectively.

FORMNEXUS-GPT-4 was, in most cases, effective in inferring an accurate model of the constraints on the first attempt. On average, the method reached stable constraints within **1.13** iterations. In **4** out of **30** cases was a second iteration necessary to derive a more accurate list of constraints. No instances required more than two iterations to achieve a stable constraint list.

On average, FORMNEXUS-GPT-4 produced **3.77** constraints per input field. In the constraint validation phase, approximately **26%** of these constraints were invalidated on average, showing that these invalidated constraints were not factored into the application's design by the developers. In total, FORMNEXUS-GPT-4 generated **389** constraints, which averages around **13.0** constraints for each form. FORMNEXUS-LLAMA 2 produced **13.11** constraints per input field, **45.3** per each form, with a total of **1359** constraints, where on average around **76%** of the constraints were invalidated.

4.4 RQ2: Comparison

The data presented in Figure 6 demonstrate that FORMNEXUS-GPT-4, achieves an average coverage rate of **89%**, which significantly surpasses the results achieved by the baselines; The static method attained a 57% coverage rate, while Crawljax only attained a 30% coverage rate. The standalone LLAMA 2 and GPT-4 models managed a coverage rate of 35% and 71%, respectively. FORMNEXUS-LLAMA 2 can improve its accuracy to 51%. Therefore, our technique represents an 25% improvement in FSS coverage over the next best-performing baseline, namely standalone GPT-4.

It is worth noting that there were 3 out of 30 (10%) instances where GPT-4 could not generate any viable values for form inputs. Two of these cases were due to the context size of the form being exceeded, rendering the GPT-4 model unable to produce meaningful outputs. In another case, the response generated by GPT-4 was nonsensical and could not be interpreted in a useful way. Similarly, LLAMA 2 was unable to produce viable responses in 14 out of 30 (46%) instances due to context size limitations. These limitations underscore the benefits of our approach. By constraining each LLM prompt to focus solely on one input and supplying contextualized information, FORMNEXUS decreases the LLM's context size. Additionally, by structuring the constraint and value generation process into distinct steps, we delegate fewer internal processing tasks to the LLM, thereby reducing the likelihood of nonsensical or unwanted outputs.

We measure the rate of successful FSSs as the *form passing rate*, presented in Figure 7. FORMNEXUS-GPT-4 was able to generate successful entries for **83**% of the forms, marking a notable **27**% improvement over GPT-4 model with a 63% passing rate. The static method, Crawljax, and QTYPIST yielded 23%, 3%, and 57% passing rates, and LLAMA 2 and FORMNEXUS-LLAMA 2 yielded 33% and 30% respectively. Their generated values often deviated from the forms' specific requirements, limiting their success to only forms with simple validation rules.

4.5 RQ3: Ablation Study

Our approach is comprised of multiple sub-modules, each of which contributes to the final results. In addressing RQ3, our objective is to elucidate the individual contributions of these components. Specifically, for each part of the ablation, we remove one specific module while keeping everything else the same. We utilize the FORMNEXUS-GPT-4 given its superior performance shown in the previous sections. The ablation study is conducted across all applications listed in our dataset, and the averages are presented in Table 3.

Effectiveness of FERG in Test Generation. By excluding the local textual context and relevant input context from the constraint and value generation prompts, we can quantify the extent to which FERG's information enhances the test generation results. Table 3 indicates that employing FERG and appending pertinent information to the prompt can bolster the state coverage from 82% to 89%, equating to a 9% improvement. Furthermore, the passing rate of the method increased from 70% to 83% by adding the FERG to the prompt. Even without employing FERG, FORMNEXUS-GPT-4 still significantly outperforms (82%) the standalone GPT-4 model (71%).

Table 3: Ablation Results of FORMNEXUS-GPT-4

Variation	Average FSS Coverage	Total Passing Rate
No FERG	82%	70%
No Date	83%	70%
No Feedback	87%	73%
No Form Context	88%	83%
FormNexus-GPT-4	89%	83%

This superior performance can be primarily attributed to FORM-NEXUS's structured workflow. By supplying the LLM with a set of constraints, we guide it toward identifying a broader range of potential validations on the input fields. Consequently, the LLM becomes capable of generating values that it would not have been able to produce without this additional guidance.

Inclusion of Date. A significant number of forms feature daterelated fields, many of which contain validations to ensure the provided date falls within an appropriate time. Therefore, including the current date in the prompt, as detailed in subsection 3.2, can assist with generating test cases for these forms. As demonstrated in Table 3, incorporating the date into the prompt can increase the method's coverage from 83% to 89%. However, this increase is constrained by the fact that some web forms either lack date-related validation or date-related input fields. The average improvement for forms with date fields is around 20%, compared with the 7% overall improvement. Moreover, the inclusion of date increased the passing rate from 70% to 83%.

Effects of Feedback. As indicated in Table 3, the improvement with a feedback loop is less significant than the two previous variations since the LLM infers the correct constraints of the input fields mostly during the first iteration. Nevertheless, in the cases that required more than one iteration, we noted an average of 2% improvement in the covered FSSs. Overall, the inclusion of a feedback loop is justified, as there may be numerous real-world scenarios where the LLM is unable to accurately infer the constraints on the first attempt. By incorporating feedback into the prompt, we were able to cover successful submissions more and it contributed to increasing the passing rate from 73%.

Effects of Form Context. According to data in Table 3, form context (see Figure 5) provides a slight advantage in FFS coverage but no effect on the passing rate. This is mainly because the semantic constraints of most of the input fields are reflected in the FERG and can be inferred independently from the form context.

5 DISCUSSION

Variations in FORMNEXUS Effectiveness. The improvement in FSS coverage achieved by FORMNEXUS compared to baseline results varies significantly across different categories of web forms. For example, query web forms, which typically lack the complex validations found in travel forms, usually consist of a single free-form text input and seldom give failure feedback. Consequently, we observed notable improvements in FSS coverage with FORMNEXUS in various categories. For instance, in the context of travel forms, FORMNEXUS-GPT-4 achieved an FSS rate of **82**%, a considerable enhancement over the 42% with GPT-4 and 36% using QTYPIST. In contrast, for query forms, the FSS coverage rates are 92% for FORMNEXUS-GPT-4, 91% for GPT-4, and 90% for QTYPIST. These findings indicate that FORMNEXUS is more effective in enhancing coverage rates in complex scenarios.

Threats to Validity. One external threat to the validity of our work is the representativeness of our experimental subject selection. To mitigate this threat, we chose subjects from diverse categories of web applications and included diverse web forms.

The validity of our work may also be threatened by the populated ground truth dataset. Given the inherent difficulties in fully understanding the underlying logic of real-world web applications, the numbers we have measured might not perfectly represent the actual logic of the form. To address this issue, multiple authors independently tested the web forms and consolidated their results, aiming to minimize the possibility of missing any form submission states. However, it should be noted that regardless of the actual total number of submission states, our method has consistently demonstrated a significant improvement in discovering submission states over the baselines.

6 RELATED WORK

Automated Form Filling. Research in automated form filling has progressed from heuristic-based methods [7, 10, 42, 43, 47] to machine learning techniques [11, 44], addressing challenges in web crawling [38] and automatic completion of web forms [23, 24, 26, 27, 36, 51]. Specialized strategies focus on mobile form-filling [8, 20, 30, 46], with LLMs like GPT-3 aiding in input generation [13, 32]. However, these do not encompass form-testing like FORMNEXUS, which also integrates FERG and GPT-4 for semantic comprehension of web forms.

Sparse literature on test generation for web forms includes Santiago et al.'s machine learning approach for extracting web form semantics [39], but it lacks the flexibility and real-world application of FORMNEXUS. Form understanding is further explored in projects like OPAL [18] and studies like Zhang et al. [50], focusing on classifying input fields using various features. However, they fall short in identifying interrelationships between form elements, which is vital for capturing form complexities.

LLMs. LLMs have been pivotal in various web-related tasks such as HTML understanding [22], information extraction [31], and web page summarization [15]. Language models specific to HTML like HTLM [6], Webformer [21], DOM-LM [17], and MarkupLM [29] have been developed. Their integration into software testing has been innovative [25, 28, 34, 40, 41, 48]. Mind2Web introduces a dataset with real-world web applications using LLMs, but its understanding of form semantics is limited [16]. In contrast, FORMNEXUS leverages FERG to enrich web form semantics, enhancing form filling effectiveness.

7 CONCLUSION

Web form testing has been an under-explored area of research, despite its considerable potential utility for developers. In this paper, we introduced FORMNEXUS, a novel technique for automatically generating test cases for web forms. Our approach leverages a unique technique to discern the context of input fields within forms by creating a graph called FERG. We leverage these contexts within a workflow to generate constraints for input fields, and subsequently, to generate test cases based on these constraints using LLMs. We demonstrate that FORMNEXUS achieves an impressive **89**% submission state coverage and an **83**% form passing rate, outperforming other techniques by a minimum of 25% in coverage and 27% in passing rate.

For future work, we plan to expand our dataset and improve our work to accommodate multi-step web forms. Additionally, we plan to investigate different Graph Neural Network-based architectures for generating embeddings, with a goal to further enhance the effectiveness of FERG in identifying semantic relationships.

8 DATA AVAILABILITY

The implementation of our technique, FORMNEXUS, has been made publicly accessible [3]. This includes a comprehensive codebase, scripts, and a detailed collection of constraint templates and system prompts used for LLMs. Furthermore, the repository offers extensive documentation on the applications and web forms utilized in our evaluations, along with the ground truth dataset.

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