The Ontological Key: Automatically Understanding and Integrating Forms to Access the Deep Web

Tim Furche · Georg Gottlob · Giovanni Grasso · Xiaonan Guo · Giorgio Orsi · Christian Schallhart

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Abstract Forms are our gates to the web. They enable us to access the deep content of web sites. Automatic form understanding provides applications, ranging from crawlers over meta-search engines to service integrators, with a key to this content. Yet, it has received little attention other than as component in specific applications such as crawlers or meta-search engines. No comprehensive approach to form understanding exists, let alone one that produces rich models for semantic services or integration with linked open data.

In this paper, we present OPAL, the first comprehensive approach to form understanding and integration. We identify form labeling and form interpretation as the two main tasks involved in form understanding. On both problems OPAL pushes the state of the art: For form labeling, it combines features from the text, structure, and visual rendering of a web page. In extensive experiments on the ICQ and TEL-8 benchmarks and a set of 200 modern web forms OPAL outperforms previous approaches for form labeling by a significant margin. For form interpretation, OPAL uses a schema (or ontology) of forms in a given domain. Thanks to this domain schema, it is able to produce nearly perfect (> 97% accuracy in the evaluation domains) form interpretations. Yet, the effort to produce a domain schema is very low, as we provide a Datalog-based template language that eases the specification of such schemata and a methodology for deriving a domain schema largely automatically from an existing domain ontology. We demonstrate the value of OPAL’s form interpretations through a light-weight form integration system that successfully translates and distributes master queries to hundreds of forms with no error, yet is implemented with only a handful translation rules.

1 Introduction

Unlocking the vast amount of data in the deep web for automatic processing has been a central part of “web as a database” visions in the past. The web offers unprecedented choice and variety of products, but we lack tools to make these wealth of offers easily manageable. Say you are looking for a flat. Aren’t you tired of filling registration forms with your search criteria on the websites of hundreds of local agencies? You fear to miss the site with the very best offer? Wouldn’t you wish to automatize these tiresome tasks? To unlock this data for automatic processing requires two keys: a key that allows us through the human-centric, scripted form interfaces of the web and a key to identify offers among all the other data on the web. In this paper, we focus on the former: A key to web forms, the gates to the deep web. Since these gates are designed for human admission, they pose a plethora of challenges for automatic processing: Even web forms within a single domain denote search criteria differently, e.g., “address”, “city”, “town”, and “neighborhood” all refer to locations, while other terms denote different criteria ambiguously, e.g., “tenure” might refer to the choice either between “freehold” vs. “leasehold” or between “buy” vs. “rent”. Moreover, web forms present their criteria in different manners, e.g., for a choice among several options, a form may contain either a drop-down lists or a set of check boxes. Automatically understanding these variants to pass through forms is needed by a broad range of applications: crawling and surfacing the deep web [27, 20, 3], interface and service integration [35], matching interfaces across domains [7, 32], classifying the domain of web databases [4] for web site classification, sampling the contents of web databases [21, 2], ontology enrichment and knowledge-base construction [25], question answering for the deep web [19]. In web engineering, automated form understanding contributes, e.g., to web accessibility and us-
ability [16], web source integration [10], automated testing on form-related web applications.

The form understanding problem has attracted a number of approaches [35][32][10][23][17]. These approaches turn observations on common features of web forms (in general, across domains) into specifically tailored algorithms and heuristics, but generally suffer from three major limitations:

1. Most approaches are domain independent and thus limited to observations that hold for forms across all domains. This limitation is acknowledged in [35][23][17], but addressed only through domain specific training data, if at all. Our evaluation supports [17] in that a set of generic design rules underlies all domains, but that specific domains parameterise or adapt to these rules in ways uncommon to other domains.

2. Most approaches are limited in the classes of features they use in their heuristics and often based on a single sophisticated heuristics using one class of features, e.g., only visual features [10] or textual and field type features in [17].

3. Heuristics are translated into monolithic algorithms limiting maintainability and adaptability. For example, [32] and [23] encode specific assumptions on the spatial distance and alignment of fields and labels. [17] employs hard-coded token classes for certain concepts such as “min”, “from” vs. “max”, “to”.

To overcome these limitations, we present OPAL (ontology based web pattern analysis with logic), a domain-aware form understanding system that combines visual, textual, and structural features with a thin layer of domain knowledge. The visual, textual, and structural features are combined in a domain-independent analysis to produce a highly accurate form labeling. However, for most applications what is actually needed is a form model consistent with a (reference) schema of the forms in the given domain, where all the fields are associated with given types. In OPAL, the domain schema is not only used to classify the fields and segments of the form model, but also to improve the form model based on a set of structural constraints that describe typical fields and their arrangement in forms of the domain, e.g., how price ranges are presented in forms. To ease the development of these domain ontologies, OPAL extends Datalog with templates to enable reuse of common form patterns in forms, e.g., how ranges (of any type) are presented in forms. With this approach, OPAL achieves nearly perfect analysis results (>97% accuracy).

In contrast to previous approaches, OPAL produces rich form models, typed to the given domain schema: The models contain not only types (and individual) constraints for form fields, but group those fields into semantic segments, possibly with inter-field constraints. These rich models ease the development of applications that interact with these forms. To demonstrate this, we have developed a lightweight form integration system on top of OPAL that fully automatically translates queries to the domain schema into queries to the concrete forms.

1.1 Contributions

OPAL’s main contributions are:

1. Multi-scope domain-independent analysis (Section 3) that combines structural, textual, and visual features to associate labels with fields into a form labeling using three sequential “scopes” increasing the size of the neighbourhood from a subtree to everything visually to the left and top of a field. (i) At field scope, we exploit the structure of the page between fields and labels; (ii) at segment scope, observations on fields in groups of similar fields, and (iii) at layout scope, the relative position of fields and texts in the visual rendering of the page. We impose a strict preference on these scopes to disambiguate competing labelings and to reduce the number of fields considered in later scopes.

2. Domain awareness. (Section 3) OPAL is domain-aware while being as domain-independent as possible without sacrificing accuracy. This is based on the observation that generic rules contribute significantly to form understanding, but nearly perfect accuracy is only achievable through an additional layer of domain knowledge. To this end, we add an optional, domain-dependent classification and form model repair stage after the domain-independent analysis. Driven by a domain schema, OPAL classifies form fields based on textual annotations of their labels and values assigned in the domain-independent form labeling, as well as the structure of that form labeling. This classification is often imperfect due to missing or misunderstood labels. OPAL addresses this in a repair step, where structural constraints are used to disambiguate and complete the classification and reshape the form segmentation.

3. Template Language OPAL-TL. (Section 4.1) To specify a domain schema, we introduce OPAL-TL. It extends Datalog to express common patterns as parameterizable templates, e.g., describing a group consisting of a minimum and maximum field for some domain type. Together with some convenience features for querying the field labeling and its annotations, OPAL-TL allows for very compact, declarative specification of domain schemata. We also provide a template library of common phenomena, such that the adaption to new domains often requires only instantiating these templates with domain specific types. OPAL-TL preserves the complexity of Datalog.

4. Methodology for Deriving Domain Schemata. (Section 4.4) To ease the derivation of an OPAL domain schema, we present a simple, step-by-step methodology how to derive such a schema from a standard domain ontology. It is based on the observation that often the types of the proper-
ties (such as price or mileage of a car) in the domain ontology determine the configuration of form fields for that type.

(5) **Light-weight Form Integration.** (Section 5) To demonstrate the value of OPAL’s rich form models, we implement a form integration system on top of OPAL that automatically translates a master query to hundreds of concrete forms. As shown in the evaluation, even with rather simple translation rules, we achieve accurate form filling.

(6) **Extensive Evaluation.** (Section 6) In an evaluation on over 700 forms of four different datasets, we show that OPAL achieves highly accurate (> 95%) form labelings and, with a suitable domain schema, near perfect accuracy in form classification (> 97%). To compare with existing approaches (which only perform form labeling), we show that OPAL’s domain-independent analysis achieves 94 – 100% accuracy on the ICQ benchmark and 92 – 97% on TEL-8. Thus, even without domain knowledge OPAL outperforms existing approaches by at least 5%. We also show that the form integration system developed on top of OPAL is able to fill forms correctly in nearly all cases (> 93%).

We believe that OPAL offers a comprehensive solution to form understanding for most applications, but also discuss, in Section 8, the two major remaining challenges for OPAL (and form understanding, in general): highly scripted, interactive forms, increasingly also using customised form widgets, as well as richer integrity constraints and access restrictions, in particular for applications that aim to extract all of the data behind a form.

This paper is based on [12], but has been significantly extended in every part, in particular in the following three aspects: First, OPAL-TL is only sketched in [12]. Section 4 is the first formal definition of OPAL-TL, including a full rewriting semantics. It has also been extended significantly, most importantly in the supported template features (predicate variables and template groups). Second, we have added a more detailed description of an OPAL domain schema and form model to better illustrate how OPAL operates and what the output of form understanding looks like. Finally, we have implemented a full, though light-weight, form integration and filling system on top of OPAL (Section 5) to demonstrate the value of OPAL’s rich models. We have also significantly extended the evaluation to show the results of the form integration, as well as to discuss where and why a small portion of forms still pose a challenge to OPAL.

1.2 OPAL: A Walkthrough

We present the OPAL approach to form understanding using the form from the UK real estate agency Colin Mason ([cmea.co.uk/properties.asp](http://cmea.co.uk/properties.asp)). Figure 1a shows the web page with its simplified CSS box model. The page contains two forms (center and left): one for detailed search and the other for quick search. OPAL is able to identify, separate, label, and classify both forms correctly yielding two (real-estate) form models. The following discussion focuses on
the search form in the center of Figure 1a, in which each of
the components (1)-(10), each of the fields (3)-(7) and the
two columns of checkboxes in (2) are enclosed in a table,
\texttt{tr}, or \texttt{td} element. Labels for each of the components such
as “Bedrooms:” appear in separate \texttt{tr}’s.

OPAL’s form understanding operates in two parts: Form
labeling and form interpretation. In the form labeling phase
fields and groups of fields (called segments) are assigned
text labels. In the form interpretation phase those text la-


\textbf{Field scope.} (Section 3.1) OPAL starts by analysing indi-


\textbf{Segment scope.} (Section 3.2) In segment scope, we in-


For each segment as a whole, OPAL associates text nodes
to create segment labels. Segment labels can be useful to re-

Layout scope. (Section 3.3) In the layout scope, OPAL further enlarges the scope of the analysis to all fields visually to the left and above a field. The primary challenge in this scope is “overshadowing”, i.e., if other fields appear in the quadrants to the left and above a field. In this example the layout scope is not needed.

The result of the layout scope is the form labeling. Notice, that the form labeling is entirely domain independent.

Domain scope. If a form model is required, the final step in OPAL produces a form model that is consistent with a given domain schema. How to derive such a domain schema and the necessary annotations is discussed in Section 4.2. It uses domain knowledge to classify and repair the labeling and segmentation from the form labeling. In the classification step, OPAL annotates fields and segments with types based on annotations of the text labels. The verification step repairs and verifies the domain model if needed. For both steps, OPAL uses constraints specified in OPAL-TL. These constraints model typical representations of types in a domain. E.g., the first field in (4) is classified as **MIN_PRICE** as we recognise this segment as an instance of a price range template. These constraints also disambiguate between multiple, conflicting annotations, e.g., fields in (6) are annotated with **order_by** and **price**, but the **price** annotation is disregarded due to the group label. Even without the group label, **price** would be disregarded as the domain schema gives precedence to **order_by** over **price** due to the observation that if they occur together, the field is likely about “order by price” and not about actual prices. Finally, a single repair is performed in this case: We collapse the two checkbox segments in (2) as they are the only children of their parent segment and both of the same type. Figure 1c shows the final field classification as produced by OPAL.

Form integration and filling. Using the form interpretation constructed in the preceding stages, OPAL is able to map a master query formulated on the domain schema into both of the concrete forms on this page (see Figure 1a). For location, the values are typed in directly. For price, the range in the master query can also be directly entered, as the concrete forms use text inputs for prices and OPAL’s form interpretation identifies the min and max price field successfully. For the bedroom number, the value from the master query is compared with the members of the check box list and the most similar is selected.

2 Approach

OPAL constructs a model of a form consistent with a domain schema. A domain schema describes how forms in a given conceptual domain, such as the UK real estate domain, are structured. OPAL divides this problem (“form understanding”) into form labeling and form interpretation. The form labeling identifies forms and their fields, arranges the fields into a tree, and labels the found fields, segments, and forms with text nodes from the page. The form interpretation aligns a form labeling with the given domain schema and thereby classifies the form fields based on their labels.

2.1 Problem Definition

Form Labeling. A web page is a DOM tree \( P = (\{U\}_{U \in \text{Unary}}, \ R_{\text{child}}, \ R_{\text{next-sibl}}, \ R_{\text{attribute}}) \) where \( \{U\}_{U \in \text{Unary}} \) are unary type and label relations, \( R_{\text{child}} \) is the parent-child, \( R_{\text{next-sibl}} \) the direct next sibling, and \( R_{\text{attribute}} \) the attribute relation. Further XPath relations (such as descendant) are derived from these basic relations as usual [6]. \( U \) contains relations for types as in XPath (element, text, attribute, etc.) and three kinds of label relations, namely tag', tags of elements and attributes, text' for text nodes containing string \( l \) and box\( b \) for elements with bounding box \( b \) in a canonical rendering of the page. For consistency with elements, we represent the value of an attribute as text child node of the attribute.

Definition 1 A form labeling of a web page \( P \) is a tree \( F \) with functions \( \Re(\text{representative}) \) and \( \La(\text{label}) \), such that \( \Re(\text{representative}) \) maps the nodes of \( F \) into \( P \). Leaves in \( F \) are mapped to form fields and inner nodes to form segments, that is a DOM element grouping a set of fields. Each node \( n \) in \( F \) is also mapped to a set \( \La(n) \) of text nodes, the \( \text{labels} \) of \( n \).

A node can be labeled with no, one, or many labels via \( \La \). The form labeling contains a representative (via \( \Re(\text{representative}) \)) for each form. A representative contains all fields (and segments) of that form. This allows OPAL to distinguish multiple forms on a single page, even if no form element is present or multiple forms occur in a single form element.

Definition 2 Given a web page \( P \), the form labeling problem (or schema-less form understanding problem) asks for a form labeling \( F \) where for each form \( f \) in \( P \)

1. there is a node \( r \in F \) such that \( \Re(\text{representative})(r) \) is a suitable representative of \( f \)
2. for each field \( e \) in \( f \), there exists a leaf node \( n_e \in F \) such that \( n_e \) is a descendant of \( r \) and \( \Re(\text{representative})(n_e) = e \) where \( \La(n_e) \) is a suitable label set for \( e \)
3. for each inner node \( s \) in \( F \) (form segment), \( \La(s) \) is a suitable set of labels for the set of fields contained in \( s \).

The suitability of a form representative \( \Re(\text{representative})(r) \) and a label set \( \La(n_e) \) is not defined formally, but needs to be evaluated by human annotators (which this, after all, aims to simulate). Our evaluation (Section 5) shows that OPAL produces form labelings \( F_j \) that match the gold standard in nearly all cases (> 95% without using any domain knowledge).

We call a form labeling complete for a web page, if, for all \( e \), \( \La(n_e) \) contains all text nodes suitable as labels for \( e \). Finding such a form labeling is correspondingly called the complete form labeling problem.
**Form Interpretation.** To define the form interpretation problem, we formalize the notion of domain schema and introduce a form model as a form labeling extended with type information consistent with a given domain schema. First, we define the part of a domain schema that gives the necessary knowledge to interpret text nodes ("annotation schema"):

**Definition 3** An annotation schema \( \Lambda = (\mathcal{A}, \preceq, \prec, (\text{isLabel}_a, \text{isValue}_a : a \in \mathcal{A})) \) defines a set \( \mathcal{A} \) of annotation types, a transitive, reflexive subclass relation \( \preceq \), a transitive, irreflexive, antisymmetric precedence relation \( \prec \), and two characteristic functions \( \text{isLabel}_a \) and \( \text{isValue}_a \) on text nodes for each \( a \in \mathcal{A} \).

For each annotation type \( a \in \mathcal{A} \), we distinguish proper labels and values, with \( \text{isLabel}_a \) and \( \text{isValue}_a \) as corresponding characteristic functions. Proper labels are text nodes, such as "Price!", describing the field type; values, such as "more than £500", contain possible values of the field. Hence isLabel\(_a\)("Price!") and isValue\(_a\)("more than £500") hold.

The \( \preceq \) relation holds for subtypes, e.g., postcode \( \preceq \) location, and the \( \prec \) relation defines precedence on annotation types used to disambiguate competing annotations. For example, an unlabeled select box with options "Choose sorting order", "By price", and "By postcode" may be annotated with order-by, price, and postcode. If order-by \( \prec \) price and order-by \( \prec \) postcode, we pick order-by.

**Definition 4** A domain schema \( \Sigma = (\mathcal{A}, \mathcal{T}, \rightarrow, \mathcal{C}_T, \mathcal{C}_A) \) defines an annotation schema \( \Lambda \), a set of domain types \( \mathcal{T} \) with (transitive, reflexive) part-of relation \( \rightarrow \), and \( \mathcal{C}_T \) and \( \mathcal{C}_A \) that map domain types to classification and structural constraints.

For example, \( \mathcal{C}_A[\text{price}] \) requires an annotation price and prohibit any annotation of a type with precedence over price (such as order-by above). The set of structural constraints \( \mathcal{C}_T(\text{price-range}) \) for a price-range segment requires a min-price and max-price field or a price-range field. We write \( S \vdash C \), if a constraint set \( C \) is satisfied by a set \( S \) of annotation or domain types. The empty constraint set is always satisfied. \( \neg \) plays an important role in the definition of the constraints, as it prescribes the structure of the types in the domain. For details on constraints and how to define them, see Section 4.

Formally, a form interpretation \( (F, \tau) \) is a form model for \( \Sigma \) if \( A(n) \vdash C(\tau) \) and child-\( \tau(n) \vdash C_T(\tau) \) for all \( n \in F, \tau \in \tau(n) \).

**Definition 5** A form interpretation \( (F, \tau) \) is a form model for \( \Sigma \) if \( A(n) \vdash C_A(\tau) \) and child-\( \tau(n) \vdash C_T(\tau) \) for all \( n \in F, \tau \in \tau(n) \).

**Definition 6** Given a domain schema \( \Sigma \) and a form labeling \( F \), the form interpretation problem asks for a form model \( (F', \tau) \) for \( \Sigma \) such that \( F' \) differs from \( F \) only in inner nodes.

Thus, form representatives, fields, and labels are shared between \( F \) and \( F' \), but the form segments may be rearranged to conform with the structural constraints of \( \Sigma \).

**Definition 7** Given a domain schema \( \Sigma \) and a web page \( P \), the (schema-based) form understanding problem asks for a form model \( (F, \tau) \) of \( P \) under \( \Sigma \), such that \( F \) is a solution of the complete form labeling problem for \( P \).

**Form Integration and Filling.** In web interface integration a query against a global domain schema is translated and executed on concrete forms. The returned data is translated into the domain schema and returned. We focus here on the
first part of the integration problem, the query translation or form integration problem, and more specifically on its optimistic variant:

Let Σ be a domain schema. Then a query Q on Σ is a set of unary constraints on T, the domain types in Σ. We consider three types of constraints: (1) Equality constraints such as \text{postcode} = \text{OX1}; (2) range constraints such as \text{price} \in [700, 1250]; (3) inclusion constraints such as \text{colour} \in \{\text{red, green, black}\}.

Definition 8: Given a domain schema Σ, a query Q on Σ, and a concrete form F, the form integration problem is the problem to translate Q into a (single) query Q′ on F such that Q′ returns all results that match Q and can be retrieved by F and that there is no other query on F with that property that returns less results.

Note, that we do not require that Q′ returns only results that match Q, but that its result set is minimal among all queries on F that return all matches for Q that can be retrieved by F. This is necessary, as there may be no query on F that is able to exactly express Q.

2.2 OPAL Architecture

OPAL is divided into three parts. Of those, two form OPAL’s form understanding: a domain-independent part to address the form labeling problem and a domain-dependent part for form interpretation according to a domain schema. The remaining part is devoted to form integration and translates queries against a domain schema into queries on concrete forms.

OPAL produces form labelings in a novel multi-scope approach that incrementally constructs a form labeling combining textual, structural, and visual features (Figure 3). Each of the three labeling scopes considers features not considered in prior scopes:

(1) In field scope, we consider only fields and their immediate neighbourhood and thus use only the DOM tree as input.

(2) In segment scope, we detect and arrange form segments into a segment tree to interleave the contained text nodes and fields.

(3) In layout scope, we broaden the potential labels of a field by searching in the layout tree, i.e., the visual rendering of the page, and assign text nodes to fields, given a strong visual relation.

Each scope builds on the partial form labeling of the previous scope and uses the information from the additional input to find labels for previously unlabeled fields (or segments). Only the segment scope adds nodes, namely form segments, whereas field and layout scope only add labels.

Finally, in the (4) form interpretation (Section 3), we turn the form labeling produced by the first three scopes into a form model consistent with a given domain schema. (i) The labeling model is extended with (domain-specific) annotations on the textual content of proper labels and values. (ii) Fields and segments of the form labeling are classified according to classification constraints in the domain schema. (iii) Finally, violations of structural schema constraints are repaired in a top-down fashion.

Types and constraints of the domain schema are specified using OPAL-TL, an extension of Datalog that combines easy querying of the form labeling and of annotations with a rich template system. Datalog rules already ease the reuse of common types and their constraints, but the template extension enables the formulation of generic templates for such types and constraints that are instantiated for concrete types of a domain. An example of a type template is the range template, that describes typical ways for specifying range values in forms. In the real estate domain it is instantiated, e.g., for price and various room ranges. In the used car domain, we also find ranges for engine size, mileage, etc. Thus, creating a domain schema is in many cases as easy as importing common types and instantiating templates, see in Section 4.

The form understanding part of OPAL is complemented with a form integration part, where we translate a given query on the domain schema into queries on concrete forms. To do so, we construct an OPAL form model as above and then use that form model to map the constraints of the given query to fields on the concrete form. The form is then filled according to the constraints. Where a constraint can not be mapped precisely, we use standard similarity techniques to find the closest, inclusive option (in case of numerical types) or just the closest option (in case of categorical types), see Section 5.
3 Form Labeling

In OPAL, form labeling is split into three scopes. Each scope is focused on a particular class of features (e.g., visual, structural, textual). The form labeling scopes, field, segment, and layout scope, use domain-independent labeling techniques to associate form fields or segments with textual labels, building a form labeling \( F \). If a domain schema is available, the form labeling is extended to a form model in the domain-dependent analysis (Section 4).

The form labeling \( F \) is constructed bottom-up, applying each scope’s technique in sequence to yet unlabelled fields. Whenever a field is labelled at a certain scope level, further scopes do not consider this field again. This precedence order reflects higher confidence in earlier scopes and addresses competing label assignments.

3.1 Field Scope

Based on the DOM tree of the input page, the field scope assigns text nodes in a unique structural relation to individual fields as labels to these fields (see Algorithm 1). It relies on the observation that, if a text node shares a sub-tree of the DOM with a single field only, then that text node is most likely related to that field. This simple observation produces a significant portion of form labels, as shown in Section 6 and is designed to produce nearly no false positives, as also verified in Section 6.

Specifically, Algorithm 1 (1) colours lines 1–6 all nodes in \( P \) that are ancestors of a field and do not have other form fields as descendants in orange. The least ancestor that violates that condition is coloured red. (2) It identifies (line 11–12) explicit HTML elements with direct reference to a form field. (4) It labels (lines 13–16) each field \( f \) with all text nodes \( t \) whose least common ancestor with \( f \) has no other form field as descendant. This includes all text nodes \( t \) in the content of \( f \) such as its values (in case of select, input, or textarea elements), since the least common ancestor of \( t \) and \( f \) is \( f \) itself. We find these text nodes in linear time due to the tree colouring.

3.2 Segment Scope

At segment scope, the labeling analysis expands from individual fields to form segments, i.e., groups of consecutive fields with a common parent, forming the segment tree (Algorithm 2). These segments are then used to distribute text nodes to unlabeled fields in that segment (Algorithm 3). At this scope, we approximate form segments through the DOM structure and the style of the contained fields. This segmentation is later adjusted to yield only form segments with a clear semantic. It is worth noting, that on many forms only very few adjustments are necessary, supporting the veracity of the approximation of semantic segments through structure and style.

Segmentation tree. We observe that the DOM is often a fair, but noisy approximation of the semantic form structure, as it reflects the way the form author grouped fields into segments. Therefore, we start from the DOM structure to find the form segments, but we eliminate all nodes that can be safely identified as superfluous: nodes without field descendants, nodes with only one child, and nodes \( n \) where all fields in \( n \) are style-equivalent to the fields in the siblings of \( n \). Two fields are style-equivalent if they carry the same class attribute (indicating a formatting or semantic class) or the same type attribute and CSS style information.

If all field descendants of the parent of an inner node \( n \) are style-equivalent, then \( n \) should be eliminated from the segment tree, as it artificially breaks up the sequence of style-equivalent fields and is thus equivalence breaking.

Definition 9 The segment tree \( P' \) of a form page \( P \) is the maximal DOM tree included in \( P \) (i.e., obtained by collapsing nodes) such that the leaves of \( P' \) are all fields and, for all its inner nodes \( n \),

1. \( \left| \{ c \in P' : R_{domain}(c, n) \} \right| > 1 \),
2. \( n \) is not equivalence breaking.
As an example, consider the DOM tree on the left of Figure 4 where diamonds represent fields and style-equivalent fields carry the same colour. On the right hand side, we show OPAL’s segment tree for that DOM. Nodes 1 and 3 from the original DOM are eliminated as they have only one child, and node 2 as it is equivalence breaking. Nodes 4 and 5 are retained due to the red field.

**Theorem 1** The segment tree $P'$ of a web page $P$ can be computed in $O(n \times d)$ with $n$ size and $d$ depth of $P$.

**Proof** Algorithm 2 computes the segment tree $P'$ for any DOM tree $P$. Its leafs are fields (as any non field leafs are eliminated in line 2–3) and any inner node must have more than 1 child (due to line 4–5), a field descendant (due to line 2–3), and not be equivalence breaking (due to lines 6–13). In lines 6–13, we compute a Representative, bearing the style prevalent among the inner node’s fields, for each inner node in a bottom-up fashion: If all field children (line 7) and the representatives of all inner children (line 8) are style-equivalent (line 9–10), we choose an arbitrary representative and collapse all inner children of that node. Note, that it suffices to compare any of the representatives with the fields in $C$ as style-equivalence is transitive. Otherwise, we assign $\perp$ as representative, which is style-equivalent neither to any node nor to itself. Thus it prevents this node (and its ancestors) from ever being collapsed. By construction, these nodes respect (1) and (2) and this property is retained in all later steps, as their subtrees are never touched again.

$P'$ is maximal: Any tree $P''$ that includes $P'$ but is included in $P$ must contain at least one node from $P$ that has been deleted by one of the above conditions. Such a node, however, violates at least one of the conditions for a segment tree and thus $P''$ is not a segment tree. This holds because the order of the node deletions does not affect the nodes deleted.

Algorithm 2 runs in $O(n \times d)$: Lines 2–3 are in $O(n)$. Lines 4–5 and lines 6–13 are both in $O(n \times d)$ as they are dominated by the collapsing of the nodes. At most, we collapse $d−2$ inner nodes and move $O(n)$ leaves $d−2$ times.

**Segment Labeling.** We extend the existing form labeling $F$ of the field scope with form segments according to the structure of the segment tree and distribute labels in regular groups, see Algorithm 3. First (lines 2–5), we create a form segment node $s$ in the form labeling for each inner node $n_i$ in the segment tree and choose $n_i$ as representative for $s$ ($\mathcal{R}(s) = n_i$). For each segment with regular interleaving of text nodes with field or segment nodes, we use those text nodes as labels for these nodes, preserving any already assigned labels and fields (from field scope). In detail, we iterate over all descendants $c$ of each segment in document order, skipping any nodes that are descendants of another segment or field itself contained in $n$ (line 13). In the iteration, we collect all field or segment nodes in $Nodes$, and all sets of text nodes between field or segment nodes in $Labels$, except those already assigned in field scope (line 14), as we assume that these are outliers in the regular structure of the segment. We assign the $i$-th text node group to the $i$-th field, if the two lists have the same size (possibly using the first group as labels of the segment, line 17–19).

Figure 5 illustrates the segment scope labeling with triangles standing for text nodes, diamonds for fields, black circles for segments, and white circles for DOM nodes not in the segment tree. The numbers indicate which text nodes are assigned as labels to which segments or fields. E.g., for the left hand segment, we observe a regular structure of (text node $+$, field $+$) and thus we assign the $i$-th group of text nodes to the $i$-th field. For the right hand segment (4), we find a subsegment (5) and field 8 that is already labeled with text node 8 in the field scope. Thus 8 is ignored and only one text node remains directly in 4, which becomes the segment

```
Algorithm 3: SegmentLabeling(DOM P, Form Labeling F)
1 \text{S} \leftarrow \text{SegmentTree}(P);
2 \text{foreach inner node } s \text{ in } S \text{ in bottom-up order do}
3 \text{create a new segment } n_i \text{ in } F;
4 \mathcal{R}(n_i) \leftarrow s;
5 \text{create an edge } (n_i, c_i) \text{ in } F \text{ for every } \mathcal{R}(c_i) \text{ child of } s;
6 \text{foreach segment } n \text{ in } F \text{ do}
7 \text{Nodes, Labels} \leftarrow \text{new List();}
8 \text{textGrp} \leftarrow \emptyset;
9 \text{foreach } c : \mathcal{R}_{\text{descendent}}(c, \mathcal{R}(n)) \in P \text{ in document order do}
10 \text{if } \exists f \in F : \mathcal{R}(f) = c \land La(f) = \emptyset \text{ then}
11 \text{if textGrp} \neq \emptyset \text{ then Labels.add(textGrp);}
12 \text{textGrp} \leftarrow \emptyset;
13 \text{Nodes.add}(c);
14 \text{else if } c \text{ is a text node } \land \exists d \in F : c \in \mathcal{L}(d) \text{ then}
15 \text{textGrp} \leftarrow \text{textGrp} \cup \{c\};
16 \text{if textGrp} \neq \emptyset \text{ then Labels.add(textGrp); textGrp} \leftarrow \emptyset;
17 \text{if Labels.size}() = \text{Nodes.size}() + 1 \text{ then}
18 \text{add Labels}()[0] \text{ to } \mathcal{L}(n);
19 \text{delete Labels}()[0] \text{ from Labels;}
20 \text{if Labels.size}() = \text{Nodes.size}() \text{ then}
21 \text{foreach } i \text{ do add Labels}[i] \text{ to } \mathcal{L}(\text{Nodes}[i]);
```
label. In 5, we find one more text node group than fields and thus consider the first text node group as a segment label. The remaining nodes have a regular structure (field, text node+) and get assigned accordingly.

3.3 Layout Scope

At layout scope, we further refine the form labeling for each form field not yet labelled in field or segment scope, by exploring the visible text nodes in the west, north-west, or north quadrant, if they are not overshadowed by any other field. To avoid false positives, we limit this search to the boundaries of the enclosing form. First, OPAL constructs a layout tree from the CSS box labels of the DOM nodes:

**Definition 10** The layout tree of a given DOM P is a tuple \((\mathcal{P}_R, <, \mathcal{w}, \mathcal{n}, \mathcal{ne}, \mathcal{e}, \mathcal{se}, \mathcal{s}, \mathcal{sw}, \text{aligned})\) where \(\mathcal{P}_R\) is the set of DOM nodes from \(\mathcal{P}, \), and \(\mathcal{w}, \mathcal{n}, \mathcal{ne}, \mathcal{e}, \mathcal{se}, \mathcal{s}, \mathcal{sw}, \text{aligned}\) are the “belongs to” (containment), west, north-west, north, north-east, relations from RCR \([22]\), and aligned \((x, y)\) holds if \(x\) and \(y\) have the same height and are horizontally aligned.

We call \(\mathcal{w}, \mathcal{n}, \mathcal{ne}, \mathcal{e}, \mathcal{se}, \mathcal{s}, \mathcal{sw}\) the neighbour relations. The layout tree is at most quadratic in size of a given DOM P and can be computed in \(O(|\mathcal{P}|^2)\). For convenience, we write, e.g., \(\mathcal{w}-\mathcal{n}-\mathcal{w}\) to denote the union of the relations \(\mathcal{w}, \mathcal{n}, \mathcal{w}\).

In cultures with left-to-right reading direction, we observe a strong preference for placing labels in the \(\mathcal{w}-\mathcal{n}-\mathcal{w}\) region from a field. However, forms often have many fields interspersed with field labels and segment labels. Thus we have to carefully consider overshadowing. Intuitively, for a field \(f\), a visible text node \(t\) is overshadowed by another field \(f'\) if \(t\) is above \(f'\) or also visible from, but closer to \(f'\). In the particular case of aligned fields, the former would prevent any labeling for these fields and thus we relax the condition.

**Definition 11** For a given text node \(t\), a field \(f'\) overshadows another field \(f\) if

1. \(f\) and \(f'\) are unaligned, \(\mathcal{w}-\mathcal{n}-(f', f)\), and \(\mathcal{w}-\mathcal{n}-\mathcal{ne}-\mathcal{e}(t, f')\)
2. \(f\) and \(f'\) are aligned and (i) \(\mathcal{w}(t, f')\) or (ii) \(\mathcal{w}-\mathcal{n}(t, f')\) and there is a text node \(t'\) not overshadowed by another field with \(\mathcal{ne}(t', f)\) and \(\mathcal{w}-\mathcal{n}(t', f)\).

To illustrate this overshadowing, consider the example in Figure 6. For field \(F_1\), \(F_2\) and \(F_3\) are overshadowed by \(F_2\) and \(F_3\) by \(F_3\), only \(F_1\) is not overshadowed, as there is no other text node that is west, north-west, or north from \(F_1\) and not overshadowed by another field.

The layout scope labeling is then produced as follows: For each field \(f\), we collect all text nodes \(t\) with \(\mathcal{w}-\mathcal{n}(t, f)\) and add them as labels to \(f\) if they are not overshadowed by another field and not contained in a segment that is no ancestor of \(f\). The latter prevents assignment of labels from unrelated form segments.

4 Form Interpretation

There is no straightforward relationship between form fields for domain concepts, such as location or price, and their structure within a form. Even seemingly domain-independent concepts, such as price, often exhibit domain specific peculiarities, such as “guide price”, “current offers in excess”, or payment periods in real estate. OPAL’s domain schemata allow us to cover these specifics. We recall from Section 2 that a form model \((\mathcal{F}, \tau)\) for a schema \(\Sigma\) is derived from a form labeling \(\mathcal{F}\) by extending \(\mathcal{F}\) with types and restructuring its inner nodes to fit the structural constraints of \(\Sigma\).

OPAL performs form interpretation of a form labeling \(\mathcal{F}\) in two steps: (1) the classification of nodes in \(\mathcal{F}\) according to the domain types \(\mathcal{T}\) to obtain a (partial) typing \(\tau_p\). This step relies on the annotation schema \(\Lambda\) and its typing of labels in \(\mathcal{F}\); (2) the model repair where the segmentation structure derived in the segmentation scope (Section 3.2) is aligned with the structure constraints of \(\Sigma\) to complete the typing.

The effort for creating an OPAL domain schema may, at the first glance, appear considerable. However, not only do we provide OPAL-TL (Section 4.1) to ease the specification of a domain schema, we also discuss in Section 4.4 how all the artefacts needed by OPAL for a new domain can be nearly automatically derived from a standard ontology of a domain (including concept labels) and a set of entity recognisers (or annotators) for instances of the concepts. We illustrate this methodology for domain instantiation along the example of the used car domain.

4.1 Schema Design: OPAL-TL

OPAL provides a template language, OPAL-TL, for easily specifying domain schemata reusing common concepts and their constraints as well as concept templates. To implement a new domain, we only need to provide (1) for each annotation type \(a\) an annotator implementing \(\text{isLabel}_a\) and \(\text{isValue}_a\) and (2) an OPAL-TL specification of the domain types with their classification and structural constraints. The latter can be derived almost mechanically from the domain types as discussed in Section 4.4.
OPAL-TL extends Datalog with template capabilities and predefined predicates for convenient querying of annotations and DOM nodes. An OPAL-TL program is executed against a form labeling $F$ and a DOM $P$. Relations from $F$ and $P$ are mapped in the obvious way to OPAL-TL. We only use child (descendant, resp.) for the child (descendant, resp.) relation in $F$. We extend document and sibling order from $P$ to $F$: follows$(X,Y)$ for $X,Y \in F$, if $R_{\text{following}}(\Re(X),\Re(Y)) \in P$ and no other node in $F$ occurs between $X$ and $Y$ in document order; adjacent$(X,Y)$, if $R_{\text{next-sibling}}(\Re(X),\Re(Y)) \in P$ or vice versa. Finally, we abbreviate text$(\Re(X))$ and tag$(\Re(X))$ as "t"$(X)$ and $t(X)$.

Annotation types and their queries. Annotations (instances of annotation types) are characterised by an external specification of the characteristic functions isLabel$_A$ and isValue$_A$ for each $a \in A$. In the current version of OPAL, these functions are implemented with simple GATE (gate.ac.uk) gazetteers and transducers, that are either provided by human domain experts or realised by access to external annotators and knowledge bases such as DBPedia and Freebase. Together they provide annotators for common domain types such as price, location, or date. Additional entity recognisers or annotators can be added easily, as described in Section 4.4.

Annotations are used in annotation queries to select fields based on annotations on their labels and the labels of their segments:

**Definition 12** For a form labeling $F$ on a DOM $P$ and an annotation schema $A$ with annotation types $A$, an **OPAL-TL annotation query** is an expression of the form $X@A\{d,p,e,m\}$ where $X$ is a first-order variable, $A \in A$, and $d$, $p$, $e$, and $m$ are annotation modifiers. An annotation query $X@A\mu$ with $\mu \subseteq \{d,p,e,m\}$ holds for $X \in [A\mu]$ with

$$[A\mu] = \{ n \in F : M_A(n) \neq \emptyset \} \setminus \text{Block}_A(A)$$

$$\text{Fields} = \{ n : \exists f \in F : n \in \Re(f) \}$$

$$M_A(A,n) = \begin{cases} \text{Allowed}_d(n) \cap A \cup \text{isLabel}_A & \text{if } p \in \mu \\ \text{Allowed}_p(n) \cap A \cup \text{isValue}_A & \text{otherwise} \end{cases}$$

$$\text{Block}_A(A) = \begin{cases} \{ n : \exists A' \neq A : [M_A(n)] \subset [M_{A'}(n)] \} & \text{if } m \in \mu \\ \{ n : \exists A' < A : [M_A(n)] \subset [M_{A'}(n)] \} & \text{if } e \in \mu \\ \emptyset & \text{otherwise} \end{cases}$$

$$\text{Allowed}_e(n) = \begin{cases} \text{isLabel}_A(n) & \text{if } d \in \mu \\ \text{isValue}_A(n) \cup \text{isLabel}_A(\text{parent of } n) & \text{otherwise} \end{cases}$$

Intuitively, an annotation query $X@A$ returns all fields labeled with a label that is annotated with $A$. If the modifier $d$ (direct) is not present, we also consider the (direct) segment parents, otherwise only direct labels are considered. If the modifier $p$ (proper) is present, only isLabel$_A$ is used, otherwise also isValue$_A$. If the modifier $e$ (exclusive) is present, a node that fulfills all other conditions is still not returned, if there are more labels with annotations of a type that has precedence over $A$. If the modifier $m$ (maximal) is present, no other type, regardless of precedence, may have more labels with annotations at the node. Since $m$ excludes strictly more nodes than $e$, a query with both $m$ and $e$ returns the same nodes as that query without $e$.

Consider the form labeling of Figure 7 under a schema with $B \prec A$. Labels are denoted with triangles, fields with diamonds, segments with circles. Labels are further annotated with matching annotation types (here always only one), with value labels drawn as outlines only. Then, $X@A\{\}$ matches 3, 4; $X@A\{e,d\}$ matches 4, but not 3 as 3 has more labels of $B$ than of $A$ and the exclusive modifier $e$ is present; $X@A\{e,p\}$ matches 3, but not 4 as the proper modifier $p$ prevents the value labels in white to be considered. The latter matches 3 despite the presence of $e$, as we consider also the labels of the parent of 3 (since the direct modifier $d$ is absent) and thus there are two $A$ labels.

Figure 8 shows a real-life example with the annotations produced by a typical set of annotators. In 8a, there are two text inputs for min and max price. However, the two labels “min” and “max” are the only directly associated text boxes and do not carry any information that indicates that these fields are about prices. This is available only when considering the segment (and thus indirect) label “Price:”. Thus, $X@\text{price}\{d\}$ returns the empty set, but $X@\text{price}\{\}$ returns the two fields. In 8b, the drop-down menu for result ordering re-
receives two price annotations, two bedroom annotations, and five order-by annotations. With order-by <price, X @ price{e}> returns the empty set, as the price annotations are “blocked” by the order-by annotations.

**OPAL-TL templates.** OPAL-TL is a Datalog-based language for the definition of reusable templates of domain concepts. Examples of such templates are basic classification rules deriving a domain type from a conjunction of annotation types or min-max range templates where we look for multiple fields with related annotations in a group and some clue that they represent a range. In general, there are two types of such templates, one for classification constraints, one for structural constraints. The former specify relationships between domain and annotation types, the latter the abstract structure of domain concepts.

**Definition 13** An **OPAL-TL template** is an expression of the form: \( T := \langle T_1, \ldots, T_k \rangle \) where \( N \) is the template name, \( T_1, \ldots, T_k \) are template variables, \( p_1 \) is a template atom, \( expr \) a boolean formula over template atoms and annotation queries. A *template atom* \( p \in t\Sigma \) consists of a first-order predicate \( p \), a sequence of terms \( t_1, \ldots, t_n \) (where \( t_i \) is either a constant or a template variable), and a sequence of terms \( s = s_1, \ldots, s_n \) where each \( s_i \) is either a constant or a first-order variable. Template and first-order variables constitute two disjoint sets. Note that, if \( t \) is empty, then a template atom is a normal first-order atom. Moreover, when all terms \( t \) are constants, we say that the template atom is *template-ground*.

Multiple rules with the same head can be used to express disjunction of their bodies. For convenience, we use \( \lor \) and \( \neg \) over conjunctions, which are translated to Datalog as usual.

As an example, the following template defines a family of constraints that associate the concept (domain type) \( C \) to a node \( N \) whenever \( N \) is labeled by an exclusive direct and proper annotation of type \( A \).

\[
\text{TEMPLATE} \quad \text{basic.concept}<C,A>\{ \text{concept}<C>N:\langle N\rangle(:N\{\text{A}(d,e,p)\}) \}
\]

An *instantiation* of a template \( tpl \) produces a set of rules where the template variables \( C_1, \ldots, C_k \) are assigned to values \( v_1, \ldots, v_k \) defined by a *template instantiation* expression of the form:

\[
\text{INSTANTIATE} \quad \langle t_1, \ldots, t_k \rangle \text{ using } \langle v_1, \ldots, v_k \rangle \quad \ldots \quad \langle v_1, \ldots, v_k \rangle
\]

For example, the following expression instantiates \( \text{basic.concept} \) replacing \( C \) with type \( \text{radius} \) and \( A \) with annotation type \( \text{radius} \)

\[
\text{INSTANTIATE} \quad \text{basic.concept}<C,A> \quad \text{using} \quad \langle \text{radius} \rangle
\]

and produces the following instantiated rule:

\[
\text{concept}<\text{radius}>(N)\langle N\rangle(:N\{\text{radius}(d,e,p)\})
\]

The full syntax of OPAL-TL is given in Figure 9 (with \( \langle \text{string} \rangle \), \( \langle \text{id} \rangle \), and \( \langle \text{var} \rangle \) as in Datalog and \( \langle \text{tvar} \rangle \), \( \langle \text{type-id} \rangle \), \( \langle \text{annot-id} \rangle \), \( \langle \text{tag} \rangle \) template variables, domain types, annotation types, and HTML tags, respectively).

The semantics of OPAL-TL is given by rewriting any set of templates \( \Sigma_T \) into Datalog programs, using assignments of template variables to constants specified by the instantiation rules, and by considering every template-ground predicate as a new first-order predicate. Due to possible occurrences of **INSTANTIATE** within templates, the instantiation must be repeated until there are no applicable **INSTANTIATE** rules. To ensure termination of the instantiation procedure, we do not allow recursive template instantiations. Properties such as safety can be easily extended from Datalog to OPAL-TL:

**Definition 14** A **OPAL-TL template** is **safe**, if every template variable that occurs in the body also occurs in the head of the template and every rule is safe, i.e., all first-order variables that occur in the head or in a negative atom in the body, also occur in a positive atom in the body.

**Proposition 1** Let \( \Sigma_T \) be a set of safe OPAL-TL templates, and let \( S \) be an assignment specified by OPAL-TL instantiation rules, then any instantiation \( \tau(\Sigma_T, S) \) is a safe Datalog program.

In contrast to safety, stratification depends also on the instantiation and is therefore defined over the expanded program as usual.

A natural question is now the complexity of computing the form model using OPAL-TL. This is related to the complexity of fact inference in OPAL-TL:

**Proposition 2** Fact inference in OPAL-TL is PTIME-complete in data complexity (when \( \Sigma_T \) and \( S \) are fixed) and EXPTIME-complete in combined complexity.
Consider a set of template atoms $D$, a set of OPAL-TL templates $\Sigma_T$ over a set of template predicates $\mathcal{R}_T$ of at most arity $k$, and an assignment $S$ of template variables to constants in a set $\mathcal{T}_T$ specified by OPAL-TL instantiation rules. The fact inference problem for $D$, $\Sigma_T$, and $S$ is to decide whether $D \cup \Sigma_T[S] \models \varphi$, where $\varphi$ is a template atom. According to Proposition 1, the problem can be reduced to fact inference in Datalog\textsuperscript{\footnote{We assume that all templates of a fixed arity $k$ are defined over a set of fixed constants.}}, i.e., deciding whether $D \cup \Sigma_D \models \varphi$ where $\Sigma_D = \tau(\Sigma, S)$ is the rewritten program. Clearly, the data complexity is PTIME-complete as for Datalog\textsuperscript{\footnote{The complexity of data complexity for Datalog\textsuperscript{\footnote{We assume that all templates of a fixed arity $k$ are defined over a set of fixed constants.}} depends on the number of facts in the program.}}. Regarding the combined complexity, recall that fact inference for a Datalog\textsuperscript{\footnote{We assume that all templates of a fixed arity $k$ are defined over a set of fixed constants.}} program $\Sigma_D$ and a set of atoms $D$ is EXP-TIME-complete since the maximum number of atoms that can be inferred is $|\mathcal{R}_D[\cdot(dom(D))]|^w$ where $\mathcal{R}_D$ is the set of predicates of $\Sigma_D$, $dom(D)$ is the domain of $D$ and $w$ is the maximum arity of predicates in $\mathcal{R}_D$. The rewriting $\tau(\Sigma_T, S)$ can generate at most $|\mathcal{R}_T[\cdot(F)]|^2$ template-ground atoms that contribute to the signature of $\Sigma_D$. Therefore, the number of atoms that can be generated is $O(2^k \cdot 2^n)$ that is still exponential. The claim follows.

4.2 Classification

Classification is based on the classification constraints of the domain schema. In OPAL, these constraints are specified using OPAL-TL to enable reuse of domain concepts and templates. For instance, in the real estate and used car domains, we identify four templates that suffice to describe nearly all classification constraints. These templates effectively capture very common semantic entities in forms and are parameterized using domain knowledge. The building blocks are a domain type (or concept) $C$ and an annotation type $A$ that is used to define a classification constraint for $C$. None of these templates uses more than one annotation type as template parameter, though many query additional (but fixed) annotation types in their bodies.

Figure [10] shows the classification templates for real-estate and used car: (1) Concept by proper label. The first template captures direct classification of a node $N$ with type $C$, if $N$ matches $\tau@A{e,p}$, i.e., has more proper labels of type $A$ than of any other type $A'$ with $A' \prec A$. This template is used by far most frequently, primarily for concepts with unambiguous proper labels. (2) Concept by segment label. The second template relaxes the requirement by considering also indirect labels (i.e., labels of the parent segment). In the real estate and used car domains, this template is instantiated primarily for control fields such as ORDER\_BY or DISPLAY\_METHOD (grid, list, map) where the possible values of the field are often misleading (e.g., ORDER\_BY may contain "price", "location", etc. as values). (3) Concept by value label. The third template also considers value labels, but only if neither the first nor the second template can match. In that case, we infer that a field has type $C$, if the majority of its direct or indirect, value or proper labels are annotated with $A$. (4) Min-max concept. Web forms often show pairs of fields representing min-max values for a feature (e.g., the number of bedrooms of a property). We specify this template with three simple rules (line 5–12), that describe three configurations of segments with fields associated with value labels only (proper labels are captured by the first two templates). It is the only template with two concept template parameters, $C$ and $C_M$ where $C_M \sqsubseteq C$ is the "minmax" variant of $C$. The first locates, adjacent pairs of such nodes or a single such node and one that is already classified as $C$. The second rule locates nodes where the second follows directly the first (already classified with $C$), has a range\_connector (e.g., "from" or "to"), and is not annotated with an annotation type with precedence over $A$. The last rule also locates adjacent pairs of such nodes and classifies them with $C_M$ if they carry a combination of $min$ and $max$ annotations.

In addition to these templates, there is also a small number of specific rules. In the real estate domain, e.g., we use the following rule to describe forms that use links (a elements) for submission (rather than submit buttons). Identifying such a link (without probing and analysis of Javascript event handlers) is performed based on an annotation type for typical content, title (i.e., tooltip), or alt attribute of contained images. This is mostly, but not entirely domain independent (e.g., in real estate a "rent" link).

\begin{align*}
\text{concept}<\text{LINK\_BUTTON}(N_1)&\Leftarrow\text{form}(F),\text{descendant}(N_1,F),\text{link}(N_1), \\ N_1@\text{LINK\_BUTTON}(d),\neg\text{descendant}(N_2,F), \\ (\text{concept}<\text{BUTTON}(N_2)\vee\text{follows}(N_1,N_2))
\end{align*}

4.3 Model Repair

With fields and segments classified, OPAL verifies and repairs the structure of the form according to structural constraints on the segments, such that it fits to the domain constraints.

\begin{align*}
\text{template\_by\_proper}\{(\text{concept}\_by\_proper}(C,A)\Rightarrow \text{concept}(N)@\text{A}{e,p}\}
\end{align*}
Fig. 11: OPAL-TL structural constraints

Structural constraints. The structural constraints and templates in the real estate and used car domains are shown in Figure 11 ( omitting only the instantiation as in the classification case). All segment templates require that there is an outlier among the siblings of the segment: outlier<>{G} holds if at least one of G’s siblings is not a C segment. (1) Basic segment. A segment is a C segment, if its children are only other segments or concepts typed with C. This is the dominant segmentation rules, used, e.g., for ROOM, PRICE, or PROPERTY_TYPE in the real estate domain. (2) Minmax segment. A segment is a C segment, if it has at least two field children typed with CM where CM ⊆ C is the minmax type for C. This is used, e.g., for PRICE and BEDROOM range segments. (3) Segment with mandatory unique. A segment is a C segment, if its children are only segments or concepts typed with C except for one (mandatory) field child typed with U where U ⊈ C. This is used, e.g., for GEOGRAPHY segments where only one RADIUS may occur.

Repairing form interpretations. The classification yields a form interpretation F, that is, however, not necessarily a model under Σ, and may contain violations of structural constraints. We adapt the types of fields and segments and the segment hierarchy of F with the rewriting rules described below to construct a form model compliant with Σ. OPAL performs the rewriting in a stratified manner to guarantee termination and introduces at most n new segments where n is the number of fields in the form.

(1) Under Segmentation: If there is a segment n with type t such that C_T(t) requires additional child segments of type t_1,…,t_k ≐ ∅ C-T(n), we try to partition the children of n into k + 1 partitions P_1,…,P_k,P_{n+1} such that P_i ≐ C_T(t_i) and P_i ∪ {t_1,…,t_k} ≐ C_T(t_i). For each P_i we add a new segment node as child of n, classify it with t_i, and move all nodes assigned to P_i from n to that segment. If there is a segment n without type or with type t, but for which child-T(n) ≠ C-T(t) and the above case can not be applied, then that segment may be split: If there are non-overlapping subsequences C_i of children of n, such that all children of n are covered for, and for each C_i, there is a type t_i such that the types of C_i satisfy the constraints for t_i, then we replace n with a sequence of segments, one for each C_i typed with t_i.

In practice, few cases of multiple under segmentations occur at the same node and we can limit the search space using a total order on T. We observe that the number of segments is bounded by the number of fields in the form and provide a pool of unused segments in the segmentation. This avoids the need for value invention in the model repair.

(2) Over Segmentation: If there is a segment n of type t with children c_1,…,c_k such that ∪_{child-T(c)} ∪ ∪_{t′ ∈ T(n′)} T(n) ≐ C_T(t) where C is the set of children of n without c_1…c_k, then we move the children of each c_i to n and delete all c_i.

(3) Under Classification: If there is a segment n of type t with untyped children c_1,…,c_k and corresponding types t_1,…,t_k such that child-T(n) ∪ {t_1,…,t_k} ≐ C_T(t) and, for each c_i, child-T(c_i) ≐ C_T(t_i) holds, then we type c_i with t_i.

(4) Over Classification: If there is a segment node n of type t with child c typed t_1 and t_2 such that {t_1} ∪ ∪_{t′ ∈ T(c')} T(t) ≐ C_T(t) where C is the set of children of n without c, we drop t_2 from T(c).

(5) Miss Classification: If there is a node n of type t where child-T(n) ≠ C_T(t), then we delete the classification of n as t.

Figure 12 shows the segmentation and classification OPAL obtains for this form before model repair. There are several problems with this segmentation:

(1) The min.price and max.price fields are not arranged into a range segment as no such node is present in the DOM. This is a case of under segmentation. Following the segment-range constraint, OPAL introduces a price range segment to include both fields as in Figure 13.

(2) The four radio buttons under “order by” are of two different domain types, i.e., ORDER_BY for the first two and DISPLAY for the last two. Due to concept-by-segment from Figure 10 and the segment label “order by”, the last two would also get classified as ORDER_BY, if not for display ≐ ORDER_BY.

This is an example of the second case of under segmentation, where OPAL needs to split the existing segment as it is not supported by a structural constraint, but there are
subsequences of children that can form valid segments (Figure 13b).

(3) As a result of the original segment with four radio buttons grouped together, the last two radio buttons in the four are also typed as ORDER_BY in addition to their display type. OPAL resolves this over classification by removing the ORDER_BY following the restructuring of the segment.

(4) The PROPERTY_TYPE segment is subdivided into two segments in the original segmentation, since OPAL identifies no style-equivalence among the six check boxes due to lack of similarity. However, two segments of PROPERTY_TYPE can not be contained in a single parent segment (due to outlier). Thus, the two segments are removed with all their children directly contained in the larger segment (Figure 13c). This is an example of over segmentation.

(5) The segmentation obtained at segment scope preserves the two DOM nodes representing two form rows. However, in the domain schema, these nodes do not carry meaning, and thus are treated as over segmentation and removed.

4.4 Domain Instantiation: Methodology and Example

In this section, we demonstrate how to derive an OPAL domain schema, which includes form specific concepts, from a given standard ontology of a domain. This is the typical way to instantiate a domain for use with OPAL.

Figure 14 shows a simple ontology for the used car domain (in the UK). Note, that most search forms are about searching for entities (double border in Figure 14) by their properties (single border) such as price or mileage of a car. Therefore, most of the types in an OPAL domain schema correspond to such properties of entities in the domain.

We observe that properties can be roughly distinguished into numerical, categorical, and free text according to their range and that these distinctions dictate to a large extent the expected form fields for searching by those properties. For a numerical property we expect, e.g., either a single text input or slider, two min-max fields for entering a range, or a set of checkboxes to select common values or ranges. Categorical properties, on the other hand, never exhibit range inputs.

These observations are codified in the derivation templates of Figure 15. These templates group typical instantiations for the above kinds of properties as well as for compound object types such as LOCATION in Figure 14:

(1) For an object type (e.g., ADDRESS), we instantiate only the segment<C> template, i.e., we allow segments, but not fields of this type. Such segments typically collect multiple properties of the object type, e.g., ENGINE_SIZE and FUEL_TYPE.

(2) For a free text type (e.g., ADDRESS), we instantiate only the concept_by_proper<C,A> and concept_by_value<C,A> templates that allows fields, but not segments of that type. There is usually no need for a segment in this case, as there are rarely multiple occurrences of fields for such a type. In the rare case where that is nevertheless possible, we instantiate segment<C> separately.

(3) For a categorial type (MAKE or COLOUR), we instantiate in addition to concept_by_proper<C,A> also segment<C> and the concept_by_segment<C,A>. Categorical types are often represented as single select boxes or lists of radio buttons or check boxes. For the latter, an enclosing segment is desir-
able and concept.by.segment<C, A> allows us to propagate the segment labels to the fields.

(4) For a numerical type (PRICE or seats), we also instantiate the segment_range and concept_minmax templates, enabling the classification of range segments and fields.

With these templates, we can derive an OPAL annotation and domain schema very quickly from a given domain schema such as Figure 14.

First, we normalize the ontology: If a class C has sub-classes without additional properties (type classes), we generate a new categorical property C TYPE, add all labels from the sub-classes to that property, and remove the sub-classes.

Second, we derive the annotation schema and, in particular, the necessary annotators as follows:

(1) For each concept or property c of the ontology, we create an annotation type c. All labels of c, possibly enriched with synonyms from an external knowledge base such as Wordnet, form an annotator for the proper labels of the concept (isLabelC).

(2) For categorical concepts or properties, we require a given list of instances, an existing annotator, or another entity recogniser, again possibly provided by an external knowledge base such as DBPedia or LinkedGeoData. Numerical values are treated similarly, though these often take simply the form of number in a certain range. This provides isValueC.

Third, we derive the domain schema in four steps:

(1) For each class C, add an instantiation rule for object_type<C>. In our example, this yields 6 instantiations (recall, that type classes are normalised to properties above).

(2) For each property, add an instantiation rule of corresponding type, e.g.,

\[
\text{INSTANTIATE} \text{ numeric.type}<C, C_M, A> \text{ using } \{ \text{PRICE}, \text{PRICE}_M, \text{price} \}
\]

In our example, this yields 22 instantiations (20 properties from Figure 14 and two . type properties).

(3) Determine which “presentational” fields and segments occur in the given domain and add them to the domain schema. A field or segment is presentational, if it determines the way the results are represented. In the used car and real estate domains, we identify two types of presentational fields: “order-by” and “pagination” which control the order in which the results are presented as well as the number of results per page. These presentational types are mostly shared between domains and can be easily reused thanks to OPAL-TL templates:

\[
\text{INSTANTIATE} \text{ categorical.type}<C, A> \text{ using } \\
\{ \text{ORDER_BY, order_by} < \text{PAGINATION, pagination} \}
\]

In this step, we also add generic rules that are independent of the domain, e.g., for the form itself and domain-independent form facilities such as submit buttons or generic keyword search fields.

(4) Sometimes small manual adjustments are necessary. For example, numerical types may occur with multiple units of measure or other modifiers, e.g., prices with different currencies or locations with a search radius. Such modifier fields are usually unique in their corresponding segment and thus added using the segment.with.unique<C, U> template. In
the used car domain, we can observe this for CURRENCY and RADIUS:

\[
\text{INSTANTIATE TEMPLATE segment.with.unique<C,U> using}
\{<\text{PRICE}, \text{CURRENCY}> <\text{LOCATION}, \text{RADIUS}> \}
\]

\[
\text{INSTANTIATE TEMPLATE concept.by.proper<C,A> using}
\{<\text{CURRENCY}, \text{currency}>, <\text{RADIUS}, \text{radius}> \}
\]

\[
\text{INSTANTIATE TEMPLATE concept.by.value<C,A> using}
\{<\text{CURRENCY}, \text{currency}>, <\text{RADIUS}, \text{radius}> \}
\]

Some object types, in particular LOCATION, may also be entered as a whole through free text fields and accordingly instantiate the free_text_type template for them:

\[
\text{INSTANTIATE TEMPLATE free_text_type<C,A> using}
\{<\text{LOCATION}, \text{location}> \}
\]

Finally, we need to determine part-of and precedence between types. The part-of relation is derived from the associations of the domain schema, e.g., ADDRESS \(\rightarrow\) LOCATION, POSTCODE \(\rightarrow\) LOCATION, FUEL_TYPE \(\rightarrow\) ENGINE for our case. Precedence requires some observation of cases where annotations for different types overlap. Typically, we want to give presentational types precedence over all domain types (as they often contain values such as “sort by price”). For the used car domain, we observe that \text{PAGINATION} \(\prec\) \text{ORDER_BY} and that both have precedence over all domain types. We also observe that \text{MILEAGE} and \text{RADIUS} (in locations) can have overlapping values. Though radius is only used in \text{segment.with.unique<C,U>}, \text{FOR LOCATION segments which disallow MILEAGE elements, we add MILEAGE }\prec \text{RADIUS to express a bias for MILEAGE.}

Figure 16 shows a form from the used car domain fully classified according to this domain schema.

5 Light-weight Form Integration

OPAL’s form models allow the easy implementation of many types of applications that require automatic understanding and interaction with forms, such as form integration and filling, data extraction, or web automation. As discussed in Section 2, we focus here on \text{form integration} (or filling), i.e., the part of a web integration system [14] that translates a query on the global schema (OPAL’s domain schema) to a query against concrete forms. In this section, we introduce a light-weight form integration system that performs this task fully automatically for thousands of forms in a domain, given only an OPAL domain schema. We have instantiated this system for the real estate and used car domain, but OPAL is as easily applied to other domains, since only a very limited amount of additional customisation is needed (on type variations and, possibly, similarities).

Recall, that we focus on the optimistic, single-query variant of the form integration problem: We aim for a single-query that returns all results matching the global (or master) query, but allow to return also non-matching results, if there is no more specific query that returns all matching ones.

OPAL’s form integration translates the master query into concrete queries through a small set of translation rules supported by a notion of similarity on property values. OPAL can perform form integration without any other information than what is provided by an OPAL domain schema and corresponding form model. However, it can be further improved by providing additional domain-specific information.

Similiarity on values is represented as a real-valued function on pairs of values and is based on the property type: For free-text and categorical properties, OPAL uses a mix of Levenshtein and longest common substring distance, for numeric properties a difference-based similarity. A domain schema can be enhanced by property-specific similarity function, e.g., to deal with different units of measure. A small set of such functions is provided with OPAL: for price, for distance properties, and for dates.

Translation rules use these similarity functions to translate the constraints of the master query \(Q\) into queries on the concrete forms. For each form \(F\) with form model \(M\) and constraint \(C \in Q\) on type \(T\), we retrieve the fields \(f_1, \ldots, f_n\) classified with \(T\). Let \text{values}(C) be the (possibly infinite) set of values for which \(C\) holds.

(1) Single field, single value: If \(n = 1\), \text{values}(C) = \{v\}, and \(f_i\) is a free text input, return \(f_1 = v\).
In all other cases (e.g., a select box for a set inclusion constraint), we return no constraints to avoid false negatives.

In many domains, we can observe that the same information is represented in alternative ways on different sites. E.g., the age of a car is represented by the manufacturing year on one site, whereas it can be represented by the age of a car on another site. To treat this cases, we need to be able to translate a constraint such as \( \text{AGE} = 2006 \) or \( \text{POSTCODE} = \text{OX1} \) to \( \text{TOWN} = \text{Oxford} \).

We call \text{AGE} and \text{YEAR} type variants and amend the domain schema with a value mapping for each pair of type variants. Value mappings for numerical properties are typically simple conversion functions, e.g., from different units of measure. Value mappings for categorical properties are typically realised by a query to an external database or service such as DBPedia. In our example domains, we use value mappings for conversions of metric and imperial distances as well as of postcodes to towns and other locations. To treat type variants we perform the following test and translation before the aforementioned translation rules:

\( \text{(0) Type variants.} \) If \( n = 0 \) and there is a field \( f' \) with type \( T' \) such that \( T' \) is a variant type of \( T \), we translate the values in \( C \) to \( T' \) and continue with that constraint.

With those simple rules, OPAL’s form integration manages to translate most constraints as shown in Section 6. There are, of course, still cases where the translation fails, e.g., if categorical values are mapped to ranges by some ordering such as road tax brackets or iPhone models (ordered according to year of introduction). But as demonstrated in Section 6, this light-weight simple form integration already provides us with a successful translation of a master query in the vast majority of cases.

To illustrate OPAL’s form integration, we consider the form of primelocation.com as shown in the middle of Figure 17.

\( \text{(ii) } f_1 \text{ is a select box, return } f_1 = v' \text{ where } v' \text{ is the option of } f_1 \text{ most similar to } v. \)

\( \text{(2) Multi field: If } n \geq 1, \)

\( \text{(i) values}(C) = \{v\}, \text{ and all } f_i \text{ are radio buttons (exclusive options), return } f_k = \text{true} \text{ for the } f_k \text{ that is most similar to } v. \)

\( \text{(ii) values}(C) = \{v_1, \ldots, v_k\} \text{ and all } f_i \text{ are check boxes (non-exclusive options), return } f_k = \text{true} \text{ for each } f_k \text{ where a } v_i \text{ exists such that the similarity of } f_k \text{ and } v_i \text{ is minimal among all such pairs.} \)

\( \text{(iii) and all } f_i \text{ are free-text range input fields (i.e., of type } T_M, \text{ where } T_M \text{ is the minmax type to } T), \text{ then return } f_s = v_1 \text{ for each } f_s \text{ that is a minimum input and } f_e = v_k \text{ for each } f_e \text{ that is a maximum input.} \)

\( \text{(iv) and all } f_i \text{ are select-box range input fields, then return } f_s = v_1 \text{ for each } f_s \text{ that is a minimum input where } v_1 \text{ is the most similar option of } f_s \text{ to } v_i \text{ that is smaller or equal to } v_1. \) Analog for } f_e. \)

\( \text{In all other cases (e.g., a select box for a set inclusion constraint), we return no constraints to avoid false negatives.} \)
public benchmark sets, on which we only evaluate OPAL’s form labeling. This limitation necessary to allow a comparison that is fair to existing approaches, that only label forms and do not use domain knowledge. Even with this limitation, however, OPAL outperforms previous approaches in most domains by at least 5%. We also perform an introspective analysis of OPAL to show (1) the impact of field, segment, layout, and repair in the form interpretation, (2) OPAL’s performance and scalability with increasing page size, and (3) the effectiveness of the form integration in OPAL.

We evaluate the proper assignment of text nodes to form fields using standard notions of precision, recall and F-score (harmonic mean $F = F_1 = 2PR/(P+R)$ of precision and recall). For form labeling (classification), precision $P$ is measured as the proportion of correctly labeled (classified) fields over total labeled fields, while recall $R$ is the fraction of correctly labeled fields over total number of fields. For form filling precision and recall do not apply and we therefore report the error rate as portion of total fields that are not correctly filled (i.e., either filled but with a wrong value or not filled at all, despite a corresponding constraint in the master query). For all considered datasets, we compare the extracted result to a manually constructed gold standard. We evaluate segmentation through their impact on classification, see Figure 22 and the improved performance on the two datasets where we perform form interpretation (UK real estate and used car) versus the ICQ and TEL-8 datasets.

Datasets. For the UK real estate domain, we build a dataset randomly selecting 100 real estate agents from the UK yellow pages (yell.com). Similarly, we randomly pick 100 used-car dealers from the UK largest aggregator website autotrader.co.uk. The forms in these two domains have significantly different characteristics than the ones in ICQ and TEL-8, mainly due to changes in web technology and web design practices. The usage of CSS stylesheets for layout and AJAX features are among the most relevant.

The ICQ and TEL-8 datasets cover several domains. ICQ presents forms from five domains: air traveling, (used) cars, books, jobs, (U.S.) real estate. There are 20 web pages for each of the domains, but two of them are no longer accessible and thus excluded from this evaluation. TEL-8, on the other hand, contains forms from eight domains: books, car rental, jobs, hotels, airlines, auto, movies and music records. The dataset amounts to 477 forms, but only 436 of them are accessible (even in the cached version).

6.1 Field Labeling

In our first experiment we evaluate the accuracy of OPAL’s field labeling on all four datasets, but only in the UK real estate and used car domain we employ the form interpretation to further improve the field labeling. Figure 18 shows the results. The first two bars are for the random sample datasets. For the real estate domain, OPAL classifies fields with perfect precision and 98.6% recall. Overall we obtain a remarkable 99.2% F-score. The result is similar for the used car domain, where OPAL obtain 98.2% precision and 99.2% recall, that amount to 98.7% F-score. OPAL achieves lower precision than recall in the used car domain due to the fact that web forms in this domain are more interactive: certain fields are enabled only when some other field is filled properly, yet non-field placeholders are present in the HTML to indicate that a field will appear when the other field is filled. This introduces noise to field labeling and thus classification.

For the real estate domain, our domain schema consists of a few dozen field and segment types and about 40 annotation types. Similarly, in the used car domain, there are about 30 annotation types. Creating an initial domain schema (including gazetteers and testing) takes a single person familiar with a domain and OPAL-TL roughly 1 week.

The other two entries in Figure 18 regard field labeling on ICQ and TEL-8 datasets. On these, OPAL applies only its domain-independent scopes (field, segment, scope) as no domain schema is available for these domains. Nonetheless, OPAL reports very high accuracy also on these forms, confirming the effectiveness of our domain-independent analysis. Not unexpected, OPAL performs better in the UK real estate and used car domain where domain knowledge is present, even though the forms in these datasets are on average more modern and contain more fields (10.4 and 9.2 fields per form in the real-estate and used-car dataset versus 6.5 and 7.9 fields per form for ICQ and TEL-8).

Cross Domain Comparison. We use ICQ and TEL-8 to compare field labeling in OPAL against existing approaches, on a wide set of domains. Figure 19a details the result of OPAL on each domain of the ICQ dataset. It shows perfect F-score values for the jobs domain (100%) as well as auto and air travelling (99.3% and 98.3%). For comparison,
Fig. 19: OPAL on ICQ and TEL-8 benchmark

| field       | labeling scope | layout scope |
|-------------|----------------|--------------|
| total       | 761            | 154          | 72           |
| false positives | 2              | 3            | 8            |
| %           | 0.3%           | 1.9%         | 11.1%        |

Table 1: False positives

reports 92% F-score for labeling on ICQ on average, which we outperform even in the domain most difficult for OPAL (books). [32] reports slightly better precision and recall than [10], but OPAL still outperforms it by several percents.

The results for the TEL-8 dataset are depicted in Figure 19b. Here, the overall F-score is 96.3%, again mostly affected by the performance in the books domain. Note that, especially on TEL-8, OPAL obtains very high precision compared to recall. Indeed, lower recall means OPAL is not able to assign labels to all fields, missing some of them. For comparison, [10] reports 88 – 90% overall F-score, which we outperform by a wide margin. [23] reports F-scores between 89% and 95% for four domains in the TEL-8 dataset. Though they perform slightly better on books, we significantly outperform them on the three other domains included in their results, as well as on average.

In Section 4 we discuss that OPAL prioritises field over segment over layout scope and we claim that this is due to the decreasing precision. Table 1 shows the total number of fields labeled in each scope, as well as the number and percentage of false positives among those labels. It illustrates that, indeed, the field scope produces almost no false positives (2 out of 762 fields labeled in this scope, i.e., 0.3%), the segment scope also produces very few (3 out of 154 labeled fields), and the layout scope produces most (8 out of 72 labeled fields).

What keeps OPAL from achieving 100% accuracy? Most of the cases are due to OPAL’s assumption that form labels are separate text nodes. This is evidently the case in most forms, as demonstrated by near perfect accuracy, but there are some outliers that use image only labels or merge multiple labels into one node and use whitespace to achieve the desired result. Figure 20, e.g., shows a form where “Title” and “Keyword” are a single HTML node with \&nbsp; spaces in between. While both cases are easy enough to address, they do require specific treatment and we omitted them from the version of OPAL presented here to illustrate that even without any such specifically tailored heuristics, we can achieve nearly perfect form labeling and interpretation.

Fig. 20: The Bookbeat form with source
6.2 Form Interpretation

The quality of OPAL’s form interpretation depends on the quality of the form labeling and that of the annotators. As discussed above, for this evaluation we use annotators that have been created in about 1 week for the UK real estate and used car domain. The location related annotators are based on standard sources (GeoNames and LinkedGeoData) and thus have reasonable recall, but precision is fairly low, due to the high number of locations in the UK that are homonyms to common English words (e.g., the town of “Selling”). Such noise in the value annotators, however, affects OPAL very little, as the values of form fields are only used if the labels are inconclusive and we only use the most frequent annotation type. Noise in the label values is far more likely to lead to classification errors. However, typical annotators are small lists of 5 – 10 typical labels which are easy to create and have very low noise. E.g., for bedroom labels we use just “bedroom”, “bed”, and their plural forms, for make, model, mileage and many more just “make”, “model”, “mileage”, and their plural form, resp.

With this, we achieve near perfect classification, correctly classifying most of the fields, see Table 1. Precision is 97.3% over all fields in the real estate data set (with just 24 out of 931 classified fields incorrectly classified) and recall 97.4%. This excludes 56 (or 5.5%) fields for which our domain schema does not contain a concept (usually as they appear very rarely).

Classification errors are mostly caused by ambiguity in the used form labels. For example, Figure 21 shows a form, where the “model style” field is erroneously classified as a model field by OPAL. The field has a proper label “model style” which is correctly assigned to the field in the field labeling, as are the field values “4x4”, “City Car”, etc. In the classification, we prioritise proper labels over values (as value annotators are more noisy). In most cases, this is indeed preferable, but here the proper label “model style” is annotated with model and we classify the field as model rather than car_type, as “model style” is not recognised as a label for car_type. A probabilistic classifications that combines classifications from labels and values (with a lower weight) would allow us to choose the most likely global form classification and thus to address such outliers. However, this would also increase the effort in creating a domain schema.

6.3 Contributions of Scopes

We demonstrate the effectiveness of combining different types of analysis by measuring to what extent each of our four scopes contributes to the overall quality of form understanding. We use again the two domain datasets from the previous experiment. For both we show the results for recall, though the picture is similar for precision and F-score, cf. Figure 18. As illustrated in Figure 22 for the field labeling in the real-estate dataset, the field scope already contributes significantly (67%). The Segment scope increases recall by 18%, layout scope and the repair in the form interpretation add together another 13%. Note that, the contribution of the repair in the form interpretation is more significant than that of the layout scope, indicating the importance of domain knowledge to achieve very high accuracy form understanding. In the used car domain, field scope alone is even more significant 85% (as many of the websites use modern web technologies and frameworks with reasonable structure).

6.4 Form Integration

For the evaluation of the form integration, we determine the error rate in the query translation for all forms in the used
car and real estate datasets. We use multiple master queries in both cases, using for the real estate domain combinations of location, min price, max price, and min bedroom. For the used car domain, we use combinations of location, make, model, min price, and max price. We evaluate the constraints separately and consider a constraint correctly translated, if it involves the right field on the concrete form and uses the best matching value. Overall, OPAL generates 95.6% and 93.8% correctly translated constraints.

Figure 24 presents the number of web forms where OPAL fails to translate one or more constraints incorrectly. Overall, 87% of the forms were filled perfectly, and 95% of the forms have no more than one failure. Figure 24 presents the major causes for OPAL’s failure in translating constraints: Most of example forms (possibly of a specific domain). The remaining cases divide rather evenly between errors in the form labeling (17%), in the classification or annotation (incomplete gazetteer), and an assortment of other issues, mostly browser related (e.g., scripted popovers that block access to the form fields or fields that can only be filled in a certain order).

6.5 Scalability

As discussed in Sections 3 and 4 overall the analysis of OPAL is bounded by $O(n^2)$ due to the layout scope. As expected actual performance follows a quadratic curve, but with very low constants. There is a significant amount of outliers, partially due to long page rendering time and partially due to variance in the depth and sophistication of the HTML structure. Figure 25 reports OPAL performance on all 534 forms in the combined TEL-8 and ICQ datasets. The highlight area covers 80% of the forms with 2200 nodes. OPAL requires at most 30s for the analysis (including page rendering) of these forms. Further analysis on the effect of increasing field or form numbers confirms that these have little effect and page size is the dominant factor.

7 Related Work

Form understanding has attracted a number of approaches motivated by deep web search [20,27,28], meta-search engines and web form integration [15,10,31,32,33,35] and web extraction [29,30]. We focus here on differences to OPAL, for a complete survey see [18,11]. We present related work for form understanding and form integration separately, as not all approaches consider both aspects.

7.1 Form Understanding

Form understanding approaches can be roughly categorised by the fundamental approach to the problem:

(1) The most common type encodes (mostly domain independent) observations on typical forms into implicit heuristics or explicit rules MetaQuerier [35], ExQ [32], SchemaTree [10], LITE [27], Wise-iExtractor [15], DEQUE [28], and CombMatch [16]. (2) Alternatively, some approaches LabelEx [23] and HMM [17] use machine learning from a set of example forms (possibly of a specific domain). (3) Form understanding is often done to surface the results hidden behind the form and approaches such as [20,31,27] exploit the extracted results for form understanding.

Aside of system design, OPAL primarily differs from these approaches in two aspects: (1) They mostly incorporate only one or two of OPAL’s scopes (and feature classes): MetaQuerier, ExQ, and SchemaTree mostly ignore the HTML structure (and thus field and segmentation scope) and rely on visual heuristics only; CombMatch, LITE, DEQUE, and LabelEx ignore field grouping. HMM ignores visual information. [20,31,27] use only the HTML structure, but exploit probing information, i.e., whether a submission is successful or not. (2) None of the approaches provides a proper form model classifying the form fields according to a given schema. Furthermore, no approach uses domain knowledge is used to improve the labeling or verify the classification, though LabelEx analyses domain specific term frequencies of label texts and HMM checks for generic terms, such as “min”. As evident in our evaluation, each of the scopes in OPAL considerably affects the quality of the form labeling and classifi-
cation. The fact, that each of these approaches omits at least one of the domain-independent scopes, explains the significant advantage in accuracy OPAL exhibits on Tel-8 and ICQ. Notice also that not using domain knowledge keeps these approaches out of reach of the nearly perfect field classification achieved by OPAL.

**Form understanding by observation and heuristics.** Most closely related in spirit to OPAL, though very different in realisation and accuracy, is MetaQuerier [35]. It is built upon the assumption that web forms follow a “hidden syntax” which is implicitly codified in common web design rules. To uncover this hidden syntax, MetaQuerier treats form understanding as a parsing problem, interpreting the page a sequence of “atomic visual elements”, each coming with a number of attributes, in particular with its bounding box. In a study covering 150 forms, the authors of MetaQuerier identified 21 common design patterns. These patterns are captured by production rules in grammar with preferences. MetaQuerier is not parameterisable for a specific domain. In contrast, the domain independent part of OPAL achieves nearly perfect accuracy with only 6 generic patterns by combining visual, structural, and textual features, and a simple prioritisation of these patterns by scope. OPAL’s domain dependent part allows us to adjust it for patterns specific to a domain.

ExQ [32] is similarly based primarily on visual features such as a bias for the top-left located labels comparable to OPAL, but disregards most structural clues, such as explicit for attributes of `<label>` tags and does not allow for any domain specific patterns.

Also SchemaTree [10] uses only visual features (and the `tabindex` and for attributes for fields and labels). It exploits nine observations on form design, e.g., that query interfaces are organised top-down and left-to-right or that fields form semantic groups. It uses a hierarchical alignment between fields and text nodes similar to OPAL’s segment scope and a “schema tree” where the nine observations are observed. Again, no adaptation to a specific domain is possible.

Wise-iExtractor [15] firstly tokenizes the form to obtain a high-level visual layout description (an *interface expression (IEXP)*), distinguishing text fragments, form fields, and delimiters, such as line breaks. It then associates texts and fields by computing the *association weight* between any given field and the texts in the same line and the two preceding lines, exploiting ending colons, similarities between the text and the field’s HTML name attribute, and the text-field distance. In addition, Wise also identifies generic relationships between fields: range (e.g. from, to), part (e.g. first and last name), group (e.g. radio buttons), or constraint (e.g. exact match required). However, in contrast to OPAL their form labeling only explores limited visual and textual information relying mainly on weight computation. Moreover, their domain-independent typing shares some similarities with OPAL’s templates but lacks the flexibility provided by OPAL’s domain schemata that allow us to adjust these generic types to a given domain. Though these adjustments are often small, their impact is significant, as shown in Section 6.

In [34], a (manually derived) domain schema is used to guide understanding. In contrast to OPAL, it segments a form purely based on the domain schema (called schema tree). They evaluate on a fragment (around 100-150 forms) of TEL-8 using domain schemata derived from the rest of TEL-8 (about 250 forms). This yields on the considered fragment similar accuracy as OPAL achieves on the full TEL-8, yet OPAL does not use any domain schema in this case, let alone domain schemata specifically trained on TEL-8.

**Form understanding by learning from example forms.** Where the above approaches rely on humans to derive heuristics and rules for form understanding, the following approaches use machine learning on a set of example forms. Therefore, they can also be trivially adapted to a specific domain by using domain-specific training data. The evaluation in [17], however, shows little effect of domain-specific training data: a training set from the biological domain outperforms domain-specific training set in four out of five other domains.

LabelEx [23] uses limited domain knowledge when considering the occurrence frequencies of label terms. Domain relevance of the terms occurring in a label, measured as the occurrence frequency in previous forms, is one feature used to score field-label candidates. Field-label candidates are otherwise created primarily using neighbourhood and other visual features, as well as their HTML markup. However, LabelEx does not consider field groups and thus is unable to describe segments of semantically related fields or to align fields and labels based on the group structure and does not use any domain knowledge aside of term frequency.

HMM [17] uses predefined knowledge on typical terms in forms, such as “between”, “min”, or “max”, but does not adapt these for a specific domain. HMM employs two hidden Markov models to model an “artificial web designer”. During form analysis, the HMMs are used to explain the phenomena observed on the page: The state sequences, that are most likely to produce the given web form, are considered explanations of the form. Compared to OPAL, HMM uses no visual features and no domain knowledge.

**Form understanding by probing.** All the above approaches conduct their analysis based purely on information available on the web forms. Alternatively, there is also an indirect route for form understanding by submitting the forms and analysing the query results, which often are much easier to classify (as there are many instances compared to a single form). The price is, however, that a certain amount of
analysis of those result pages is necessary. Therefore, this is primarily used in a context where such analysis is anyway required, e.g., in crawlers or data extraction systems. Typically, these approaches use an incremental approach, identifying inputs for some fields, submitting the form, analysing the result page, and then possibly restarting the whole process, now with, e.g., an increased set of input values for the form. For example, \cite{20} determines whether a field must be filled or is a “free” input by iterating over possible templates and selecting those that return sufficiently distinct result pages. This is driven by the desire to surface some representative, but not necessarily complete set of results from the web form. None of these approaches produces a sophisticated form model, but at best rough classifications of the fields and whether they are mandatory.

7.2 Form Filling and Integration

Form integration has been considered in many shapes, either as “meta-search” where a master query on a given global schema is translated to concrete forms as in \textsc{opal}, as “interface matching” where many concrete forms are integrated without a global schema (often using schema matching), or as “query generation” in the context of data extraction or crawling where the aim is to generate a set of queries to extract all or most of the data, but often not even full form understanding is performed.

Though some query generation and most interface matching approaches use form understanding, they are focused on different issues than \textsc{opal’s} form integration which is a type of “meta-search”: How to find an optimal query set that uncovers as much deep content as possible \cite{11}, how to determine if a query will produce relevant data even if only partial information about the data is available \cite{5}, how to maximize the diversity of the extracted content \cite{20}, or how to identify semantic equivalences between fields from different forms \cite{24}.

Similar to \textsc{opal}, \cite{11} fills web forms by connecting fields at the conceptual level, but with WordNet \cite{26} instead of proper annotations. Furthermore, \textsc{opal} produces more structured form model that is verified against a domain schema. \textsc{metaquerier} \cite{9}, targets the integration of web sources and tackles query translation for form filling in that context. As \textsc{opal}, \textsc{metaquerier} selects values closest to the constraint in the source query (similar to our master query). They also perform type-based query translation to map a source query to a target query considering numeric and text types, but achieve only 87% accuracy. \textsc{opal} performs form filling in a similar fashion, but also considers the number of fields for each domain type in the master query and performs significantly better (93%).

8 Conclusion and Future Work

To the best of our knowledge, \textsc{opal} is the first comprehensive approach to form understanding and integration. Previous form understanding approaches has been limited mainly by overly generic, domain independent, monolithic algorithms relying on narrow feature sets. \textsc{opal} pushes the state of the art significantly, addressing these limitations through a very accurate domain independent form labeling, exploiting visual, textual, and structural features, by itself already outperforming existing approaches. This domain independent part is complemented with a domain dependent form field classification that significantly improves the overall quality of the form understanding and produces nearly perfect form interpretations. Accurate form interpretations enables form integration; \textsc{opal} successfully realizes a lightweight form integration system, able to translate master queries to forms of a domain with nearly no errors.

Nevertheless, there remain open issues in \textsc{opal} and form understanding in general that need to be addressed for form understanding to become a reliable tool to access web data through forms with little more effort than through APIs:

(1) **Dynamic, scripted forms:** \textsc{opal} is able to understand most static forms with near perfect accuracy, but performs much worse on dynamic forms. We are already working on an extension of \textsc{opal} for dealing with dynamic, heavily scripted interfaces that combines ideas from state exploration and crawling with form understanding.

(2) **Customised form widgets:** More and more forms use customised widgets such as tree views or sliders. Though most of these cases use hidden form fields that can be analysed by \textsc{opal}, the use of fully scripted cases increases. We plan to extend \textsc{opal} to allow the customisation of the form widgets that it can recognise. However, if these cases become more common, it may become necessary to automatically explore and learn such new widget types.

(3) **Probing-based understanding:** One of \textsc{opal’s} virtues is that it achieves its near perfect accuracy without any probing, but thus from the form page alone. However, this also limits the information that \textsc{opal} can provide, and prevents the verification and repair of the form model through the results returned by a form submission. For applications that need to access the result pages (e.g., data extraction and suracing), we plan to integrate \textsc{opal} with the result page analysis system \textsc{amber} \cite{13} to further improve accuracy and to address integrity and access constraints.

(4) **Integrity and access constraints.** \textsc{opal} produces some integrity constraints through the domain schema and it’s form segmentation, e.g., dependencies between min and max fields in a range segment. We see an increase in the use of integrity constraints in forms thanks to the availability of easy-to-use client-side validation libraries. Light-weight methods for analysing and exploiting such client side vali-
dation would allow us to extend our form models with more detailed integrity constraints. This is in addition to integrity and access constraints derived from probing.

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