FLIN: A Flexible Natural Language Interface for Web Navigation

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Abstract

AI assistants have started carrying out tasks on a user's behalf by interacting directly with the web. However, training an interface that maps natural language (NL) commands to web actions is challenging for existing semantic parsing approaches due to the variable and unknown set of actions that characterize websites. We propose FLIN, a natural language interface for web navigation that maps NL commands to concept-level actions rather than low-level UI interactions, thus being able to flexibly adapt to different websites and handle their transient nature. We frame this as a ranking problem where, given a user command and a webpage, FLIN learns to score the most appropriate navigation instruction (involving action and parameter values). To train and evaluate FLIN, we collect a dataset using nine popular websites from three different domains. Quantitative results show that FLIN is capable of adapting to new websites in a given domain.

1 Introduction

AI personal assistants, such as Google Assistant, are becoming less dependent on the availability of back-end service APIs. Modern assistants can carry out a human task by directly interacting with the GUI of a website supporting it (Tech Crunch, 2019). Users issue commands to the assistant, and the assistant executes them by typing text, selecting items, clicking buttons, and navigating to different pages in the website. An essential component in these experiences is a natural language (NL) interface capable of mapping user commands (e.g., “find an Italian restaurant for 7pm”) into navigation instructions that a web browser can execute.

Recent work has proposed mapping user commands directly into low-level UI actions (button clicks, text inputs, etc.). The UI elements appearing in a webpage are embedded by concatenating their DOM attributes (tag, classes, text, etc.). Then, a scoring function (Pasupat et al., 2018) or a neural policy (Liu et al., 2018a) are trained to identify which UI element best supports a given command. Learning at the level of UI elements is effective, but only in controlled (UI elements do not change over time (Shi et al., 2017a)) or restricted (single applications (Branavan et al., 2009)) environments. This is not the case in the “real” web, where (i) websites are constantly updated and (ii) a user may ask an assistant to execute the same task in any website of their choice (e.g., ordering pizza with dominos.com, pizzahut.com, etc.). The transient nature and diversity of the web call for an NL interface that can flexibly adapt to many websites without requiring being constantly re-trained.

To achieve this goal, we take two steps. First, we conceptualize a new way of designing NL interfaces for web task execution. Instead of mapping user commands into low-level UI actions, we map them into meaningful “concept-level” actions. Concept-level actions are meant to express what a user perceives when glancing at a website UI. For example, in the homepage of opentable.com shown in Fig. 1, the action “Let’s go” (where “Let’s go” is the label of a search button) is a concept-level action that represents the “concept” of searching something which can be specified using some parameters such as a date, a time, a number of people and a search term (e.g., a location, a restaurant name or a cuisine type). Intuitively, websites in a given domain (say, all restaurant websites) share semantically-similar concept-level actions and the semantics of a human task are generally time invariant. Hence, learning at the level of concept-level actions can lead to a more flexible NL interface for web navigation.

While concept-level actions are less invariant than raw UI elements, they do not fully eliminate the problem of dealing with environments that have
Figure 1: Web task execution driven by NL commands in the OpenTable website. The user command is mapped to the concept-level action “Let’s go” whose execution causes the transition from the home to the search results page.

a variable and unknown set of actions. Concept-level actions can manifest with different representations and parameter schema across websites. For example, searching a restaurant in [opentable.com](http://opentable.com) corresponds to an action called “Let’s go” which takes up to four parameters as input; in a related website such as [yelp.com](http://yelp.com) the same concept-level action is called “search” and supports two parameters (search term and location). Moreover, websites in the same domain can support different action types (e.g., making a restaurant reservation vs. ordering food) and be updated over time.

Our second insight to tackle this problem is to leverage semantic parsing in a novel way. Traditional semantic parsing methods (Zelle and Mooney, 1996; Zettlemoyer and Collins, 2007; Branavan et al., 2009; Lau et al., 2009; Thummalapenta et al., 2012) deal with environments that have a fixed and known set of actions, hence cannot be directly applied. Instead, we propose FLIN, a new semantic parsing approach where instead of learning how to map NL commands to executable logical forms (as in traditional semantic parsing), we leverage the semantics of the symbols (name of action/parameters and parameter values) contained in the logical form (the navigation instruction) to learn how to match it against a given command. Specifically, we model the semantic parsing task as a ranking problem. Given an NL command $c$, FLIN scores the actions available in the current webpage with respect to $c$. Simultaneously, for each parameter $p$ of an action, it extracts a phrase $m$ from $c$ that expresses a value of $p$ and then, scores $p$’s values with respect to $m$ to find the best value assignment for $p$. Each action with its associated list of parameter value assignments represents a candidate navigation instruction to be ranked. FLIN learns a net score for each instruction based on corresponding action and parameter value assignment scores, and outputs the highest-scored instruction as the predicted navigation instruction.

To collect a dataset for training and testing FLIN, we built a simple rule-based Action Extractor tool that extracts concept-level actions along with their parameters (names and values, if available) from webpages. The implementation and evaluation of this tool is out of scope for this paper. In a complete system, illustrated in Fig. 1, we envision the Action Extractor to extract and pass the concept-level actions present in the current webpage to FLIN, which computes a candidate navigation instruction $N$ to be executed by an Action Executor (e.g., a web automation tool such as Selenium (2020) and Ringer (Barman et al., 2016)).

Overall, we make the following contributions: (1) we conceptualize a new design approach for NL interfaces for web navigation based on concept-level actions; (2) we build a match-based semantic parser to map NL commands to navigation instructions; and (3) we collect a new dataset based on nine websites (from restaurant, hotel and shopping domains) and provide empirical results that verify the scalability of our approach.

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1The tool processes a webpage’s DOM tree (including tree structure and DOM attributes) and its visual appearance (using computer vision techniques) to enumerate actions along with the names and values of their parameters (if any). This is an active area of research (Nguyen and Csallner, 2015; Lau et al., 2018c; Chen et al., 2020b,a).
2 Related Work

Semantic parsing \cite{Winograd1972,EtzioniWeld1994} has been a long studied problem in NLP with applications to databases \cite{ZelleMooney1996, ZettlemoyerCollins2007, Zhong2017, Ferre2017}, knowledge-based question answering \cite{BerantEtal2013, YihEtal2015}, data exploration and visual analysis \cite{SetlurEtal2016, UtamaEtal2018, LawrenceRiezler2016, GaoEtal2015}, robot navigation \cite{ArtziZettlemoyer2013, TellexEtal2011, JannerEtal2018, FriedRiezler2016, GaoEtal2015}, object manipulation \cite{FrankGoodman2012}, selection in commands \cite{GollandEtal2010, SmithEtal2011, JannerEtal2018, GuuEtal2017, FriedRiezler2016}, language game playing \cite{WangEtal2016}, UI automation \cite{BranavanEtal2009, LauEtal2009, ThummalapentaEtal2012, FazziniEtal2018, ZhaoEtal2019}. Most of these approaches assume environments with a fixed and known set of actions, while we deal with variable and unknown sets of actions.

Work on NL-guided web navigation includes learning tasks from demonstrations \cite{AllenEtal2007}, building reinforcement learning agents \cite{ShiEtal2012, FazziniEtal2018, ZhaoEtal2019}, semantic parsing \cite{Winograd1972, Etzioni1996}, robot navigation \cite{ArtziZettlemoyer2013, TellexEtal2011}, task flows from APIs \cite{WilliamsEtal2019}. These approaches assume different problem settings and deal mainly with low-level web actions or API calls. Unlike FLIN, they are not scalable across websites.

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4 The FLIN Model

The task of solving the above semantic parsing problem can be decomposed into two sub-tasks: (i) \textbf{action recognition}, i.e., recognizing the action \(a \in A_w\) intended by \(c\), and (ii) \textbf{parameter recognition and value assignment}, i.e., deciding whether a parameter of an action is expressed in \(c\) and, if so, assigning the value to that parameter. A parameter is expressed in \(c\) by a mention (word or phrase). For example, in Fig. \[1\] “me and my friend” is a mention of parameter “people” in \(c\) and a correct parsing should map it to the domain value “2 people”. Thus, the second sub-task involves first extracting a mention of a given parameter from \(c\) and then, matching it against a set of domain values to find the correct value assignment. For an open-domain parameter, the extracted mention becomes the value of the parameter. For closed-domain parameters, the domain is bounded and consists of a finite set of values that \(p\) can take; the set is imposed by the web UI, such as the available colors and sizes for a product item or the reservation times for a restaurant. For open-domain parameters, the domain is in principle unbounded, but, in practice, it consists of all words/phrases which can be extracted from \(c\). With reference to Fig. \[1\] the “let’s go” (search) action has \(n_a = \{\text{“let’s go”}\} \) and \(P_a = \{\text{“time”}, \text{“date”}, \text{“people”}, \text{“location, restaurant, or cuisine”}\} \). The first three parameters are closed-domain and the last one (the search term) is open-domain. The Action Extractor module (Fig. \[1\]) names actions and parameters after labels and texts appearing in the UI (or, if absent, using DOM attributes); it also automatically scrapes values of close-domain parameters.

Given the above setting, our goal is to map an NL command \(c\) issued in \(w\) into a navigation instruction \(N\), consisting of a correct action name \(n_a\) corresponding to action \(a \in A_w\) and an associated list of \(m \leq |P_a|\) correct parameter-value assignments, given by \(\{(p_i = v'_j) \mid p_i \in P_a, v'_j \in \text{dom}(p_i), 0 \leq i \leq K, 1 \leq j \leq |\text{dom}(p_i)|\} \).
Figure 2: Architecture of FLIN’s Action Scoring, Parameter Mention Extraction and Parameter Value Scoring components [BERT block diagram courtesy: Devlin et al. (2019)].

**Parameter Mention Extraction**, which extracts the mention (phrase) from the command for a given parameter ($4.2$); (3) **Parameter Value Scoring**, which scores a given mention with a closed-domain parameter value or rejects it if none of the domain values can be mapped to the mention ($4.3$); and (4) **Inference**, which takes the scores of actions and parameter values and infers the action-parameter-value assignment with the highest score as the predicted navigation instruction ($4.4$).

### 4.1 Action Scoring

Given a command $c$, we score each action $a \in A_w$ to measure the similarity of $a$ and $c$’s intent. We loop over the actions in $A_w$ and their parameters to obtain a list of action name and parameters pairs $(n_a, P_a)$, and then score them with respect to $c$.

To score each $(n_a, P_a)$, we learn a neural network based scoring function $S_a(.)$ that computes the similarity between $c$ and the pair. We represent $c$ as a sequence $\{w_1, w_2, ..., w_R\}$ of $R$ words. To learn a vector representation of $c$, we first convert each word $w_i$ into corresponding one-hot vectors $x_i$, and then learn embeddings of each word using an embedding matrix $E_w \in \mathbb{R}^{d \times |V|}$ as: $v_i = E_w \cdot x_i$, where $V$ is the word vocabulary. Next, given the word embedding vectors $\{v_i | 1 \leq i \leq |R|\}$, we learn the forward and backward representation using a Bi-directional Long Short Term Memory (Bi-LSTM) network (Schuster and Paliwal, 1997), as:

$$\vec{h}_f = LSTM_c \left( v_i, \vec{h}_{t-1} \right)$$

$$\vec{h}_b = LSTM_c \left( v_i, \vec{h}_{t+1} \right)$$

(1)

Let the the final hidden state for forward LSTM and backward LSTM be $\vec{h}_R$ and $\vec{h}_1$ respectively, after consuming $\{v_i | 1 \leq i \leq |R|\}$. Then, we learn a joint representation of $c$ as $\vec{v}_c = [\vec{h}_R ; \vec{h}_1] \in \mathbb{R}^{2d}$, where $[;]$ denotes concatenation.

Next, we learn a vector representation of $(n_a, P_a)$. We use the same word embedding matrix $E_w$ and Bi-LSTM layer (Equation [1]) to encode the action name $n_a$ into a vector $\vec{v}_a = BiLSTM(n_a)$. Similarly, we encode each parameter $p \in P_a$ into a vector $\vec{v}_p = BiLSTM(p)$, and then compute the net parameter semantics of action $a$ as the mean of the parameter vectors, given by $\vec{v}_p = mean\{\vec{v}_p | p \in P_a\}$. Finally, to learn the overall semantic representation of $(n_a, P_a)$, we concatenate $\vec{v}_a$ and $\vec{v}_p$ and learn a combined representation using a feed-forward (FF) layer as:

$$\vec{v}_{ap} = tanh(W_a \cdot [\vec{v}_a; \vec{v}_p] + b_a)$$

(2)

where $W_a \in \mathbb{R}^{4d \times 2d}$ and $b_a \in \mathbb{R}^{2d}$ are weights and biases of the FF layer.

Given $\vec{v}_c$ and $\vec{v}_{ap}$, we compute the intent similarity between $c$ and $(n_a, P_a)$ using cosine similarity as:
From BERT, we obtain the mention start and end vector for each token \(i\) and a mention end vector \(j\). The probability \(P\) is used to compute the end probability. The parameters of \(S_a(\cdot)\) are learned by minimizing a margin-based ranking objective \(L_a\), which encourages the scores of each positive \((n_a, P_a)\) pair to be higher than those of negative pairs in \(w\):

\[
L_a = \sum_{q \in Q^+} \sum_{q' \in Q^-} \max\{S(q') - S(q) + 1, 0\} \tag{4}
\]

where, \(Q^+\) is a set of positive \((n_a, P_a)\) pairs in \(w\) and \(Q^-\) is a set of negative \((n_a, P_a)\) pairs obtained by randomly sampling \(N_I\) number of action name and parameter pairs (which are not in \(Q^+\) in \(w\).

### 4.3 Parameter Value Scoring

Once the mention \(m_p\) is extracted for a closed-domain parameter \(p\), we learn a neural network based scoring function \(S'_p(\cdot)\) to score each \(p\)'s value \(v' \in \text{dom}(p)\) with respect to \(m_p\). If \(p\) is open-domain, parameter value scoring is not needed.

The process is similar to that of action scoring, but, in addition to word-level and lexical-level similarities, we also compute character-level and lexical-level similarity between \(v'\) and \(m_p\). In fact, \(v'\) and \(m_p\) often have partial lexical matching. For example, given the domain value “7:00 PM” for the parameter “time”, possible mentions may be “7 in the evening”, “19:00 hrs”, “at 7 pm”, etc., where partial lexical-level similarity is observed. However, learning word-level and character-level semantic similarities is also important as “PM” and “evening” as well as “7:00 PM” and “19:00” are lexically distant to each other, but semantically closer.

#### Word-level semantic similarity.

To compute word-level similarity between \(m_p\) and \(v'\), we use the same word embedding matrix \(E_w\) used in action scoring to learn the word vectors for both \(m_p\) and \(v'\). Then, we use a Bi-LSTM layer (not shared with Action Scoring) to encode mention (value) into a word-level representation vectors \(v_w^m\) \((v_w^{v'})\). Finally, the word-level similarity between \(m_p\) and \(v'\) is computed as

\[
S_w^m(p, v') = \frac{1}{2} \left[ \text{cosine}(v_w^m, v_w^{v'}) + 1 \right] \tag{5}
\]

#### Character-level semantic similarity.

To compute character-level similarity between \(m_p\) and \(v'\), we use a character embedding matrix \(E_c\) to learn the character vectors for each character composing the words in \(m_p\) and \(v'\). To learn the character-level vector representation \(v_{char}^m\) of \(m_p\), we first learn the word vector for each word in \(m_p\) by composing the character vectors in sequence using a Long Short Term Memory (LSTM) network \(\text{LSTM}\) and then, compute the word vectors for all mention words using a BiLSTM layer to obtain \(v_{char}^m\). Similarly, the character-level vector representation \(v_{char}^{v'}\) of \(v'\) is obtained. Next, we compute the character-level similarity between \(m_p\) and \(v'\) as

\[
S_p^c(m_p, v') = \frac{1}{2} \left[ \text{cosine}(v_{char}^m, v_{char}^{v'}) + 1 \right] \tag{6}
\]
Lexical-level similarity. To compute lexical-level similarity between \( m_p \) and \( v' \), we use a fuzzy string matching score (using the Levenshtein distance to calculate the differences between sequences)\(^4\) and a custom value matching score which is computed as the fraction of words in \( v' \) that appear in \( m_p \); then we encode the two similarity scores (each score \( \in [0, 1] \)) as a vector denoted as \( S_p^{\text{lex}}(m_p, v') \in \mathbb{R}^2 \).

Net value-mention similarity score. Finally, we learn a net similarity score between \( m_p \) and \( v' \) as the mean of the above three scores as \( S_p(m_p, v') = \text{mean}\{S_p^{\text{ed}}(m_p, v'), S_p^{\text{char}}(m_p, v'), S_p^{\text{lex}}(m_p, v')\} \).

The parameters of \( S_p(\cdot) \) are learned by minimizing a margin-based ranking objective \( \mathcal{L}_p \), which encourages the scores \( S_p(\cdot) \) of each mention and positive value pair to be higher than those of mention and negative value pairs for a given \( p \), and can be defined in the similar way as the previously defined \( \mathcal{L}_a \) (see §4.1).

4.4 Inference

The inference module takes the outputs of Action Scoring, Parameter Mention Extraction and Parameter Value Scoring to compute a net score \( S_{ap}(\cdot) \) for each action \( a \in A_w \) and associated list of parameter value assignments combinations and then, use \( S_{ap}(\cdot) \) to predict the navigation instruction, as discussed below.

Parameter value assignments. We first infer the values to be assigned to each parameter \( p \in P_a \), where the predicted value \( \hat{v}_p \) for a closed-domain parameter \( p \) is given by \( \hat{v}_p = \text{arg max}_{v' \in \text{dom}(p)} S_p(m_p, v') \) provided \( S_p(m_p, v') \geq \rho \). Here, \( \rho \) is a threshold score for parameter value prediction which is tuned empirically on a validation dataset used for training \( S_p(\cdot) \).

While performing the value assignments for parameter \( p \), we consider \( S_p(m_p, \hat{v}_p) \) as the confidence score for \( p \)'s assignment. If \( S_p(m_p, v') < \rho \) for all \( v' \in \text{dom}(p) \), we consider the confidence score for \( p \) as 0 and in such case \( p \) is discarded implying \( m_p \) refers to a value which does not exist in \( \text{dom}(p) \); hence, no value assignment is done. If \( p \) is an open-domain parameter, \( m_p \) is inferred as \( \hat{v}_p \) with a confidence score of 1. Otherwise, if no mention is extracted for \( p \), \( p \) is dropped.

If all \( p \in P_a \) are discarded from the prediction for a parametrized action \( a \in A_w \), we discard \( a \), as \( a \) no longer becomes executable in \( w \).

Once we get all confidence scores for all value assignments for all \( p \in P_a \), we compute the average confidence score \( \overline{S}_p(P_a) \), and consider it to be the net parameter value assignment score for \( a \).

Navigation instruction prediction. Next, we compute the overall score for a given action \( a \) and associated list of parameter value assignments as:

\[
S_{ap} = \alpha \cdot S_a(c, n_a, P_a) + (1 - \alpha) \cdot \overline{S}_p(P_a) \tag{7}
\]

where \( \alpha \) is linear combination coefficient (empirically tuned). We infer the action and associated list of parameter value assignments combination with highest \( S_{ap} \) score as the predicted navigation instruction for command \( c \).

5 Evaluation

We evaluate FLIN on nine popular websites from three representative domains: (1) Restaurants (R), (2) Hotels (H), and (3) Shopping (S). For each website, we collect labelled datasets (see §5.1). To evaluate the generalization capability of FLIN, we perform in-domain cross-website evaluation. Specifically, we train one FLIN model for each domain using one website, and test on the other (two) websites in the same domain. Ideally, a single FLIN model could be trained by merging the training datasets of all three domains and applied to all test websites. We choose to perform domain-specific training and evaluation in order to better analyze how well FLIN leverages the semantic overlapping of concept-level actions (that exists across in-domain websites) to scale to new websites. We discard cross-domain evaluation as the semantics of actions and parameters do not significantly overlap across \( R, H \) and \( S \).

5.1 Experimental Setup

Datasets. We collect two types of datasets: (i) Nav-Dataset, a dataset of command and navigation instruction pairs, and (ii) Diag-dataset, a dataset of real user utterances extracted from existing dialogue datasets paired with navigation instructions.

To collect Nav-Dataset, given a website and a task it supports, using our Action Extractor tool, we enumerate all actions present in the pages related to the task. In OpenTable, for instance, we find 8 pages related to the task “making a restaurant reservation”, including the search page, the search

\[\text{pypi.org/project/fuzzywuzzy/}\]
We use this dataset only for evaluation purposes. We construct command templates corresponding to each triplet with parameter names as placeholders. A command template may be “Book a table for [time]”. For closed-domain parameters we obtain values by automatically scraping them from webpages (e.g., \{12:00 pm, 12:15 pm, etc.\} for the time parameter), and we ask users to provide paraphrases for them (e.g., “at noon”). For open-domain parameters, we ask users to provide example values. The final dataset is assembled by instantiating command templates with randomly-chosen parameter value paraphrases and then, split into train, validation and test datasets (see Table 1 for details). Overall, we generate a total of 53,520 command and navigation instruction pairs. We use train and validation splits for model training and test splits for these sites, and we ask two annotators to write multiple parameterizations for each website. Then, we construct \texttt{<webpage\_name, action\_name, [parameter\_name]>} triplets for all actions across all sites, and we ask two annotators to write multiple command templates corresponding to each triplet with parameter names as placeholders. A command template may be “Book a table for [time]”. For closed-domain parameters we obtain values by automatically scraping them from webpages (e.g., \{12:00 pm, 12:15 pm, etc.\} for the time parameter), and we ask users to provide paraphrases for them (e.g., “at noon”). For open-domain parameters, we ask users to provide example values. The final dataset is assembled by instantiating command templates with randomly-chosen parameter value paraphrases and then, split into train, validation and test datasets (see Table 1 for details). Overall, we generate a total of 53,520 command and navigation instruction pairs. We use train and validation splits for \texttt{opentable.com}, \texttt{hotels.com} and \texttt{rei.com} for model training and test splits for these sites and other sites for in-website and cross-website evaluation (see Table 1).

The second dataset, \textit{Diag-dataset}, consists of real user queries extracted from the SGD dialogue dataset \citep{datasets2020} and from Restaurants, Hotels and Shopping “pre-built agents” of Dialogflow \citep{dialogflow.com}. We extract queries that are mappable to our web actions and adapt them by replacing out-of-vocabulary mentions of restaurants, hotels, cities, etc. with equivalent entities from our vocabulary. We manually map 421, 155 and 63 dialogue queries to navigation instructions for \texttt{opentable.com}, \texttt{hotels.com} and \texttt{rei.com} respectively. We use this dataset only for evaluation purposes.

### Hyper-parameter Settings

FLIN’s hyper-parameters are set empirically, as follows: batch-size is 50; number of training epochs for action scoring is 7; for parameter mention extraction is 3 and for parameter value scoring is 22; \(N_1 = 1\) (in Eqn 4 is sampled in every epoch); dropout is 0.1; hidden units and embedding size are 300; learning rate is 1e-4; regularization parameter is 0.001; \(\rho = 0.67; \alpha = 0.4\). Adam \citep{Kingma2014} is used for optimization. We use one Tesla P100 GPU for our experiments and Tensorflow for implementation.

### Compared Models

A direct performance comparison with other approaches is not possible as they differ in the type of output \citep{Pasupat2018} or problem settings \citep{Liu2018b}. Nonetheless, we compare various versions of FLIN that use the match-based semantic parsing approach at their core but with following differences:

1. **FLIN-embed**: a variant of FLIN that uses an embedding-based matching function for action scoring and parameter value scoring following the embedding-based model by \citep{Pasupat2018}. We use cosine similarity for computing scores.

2. **FLIN-sem**: a variant of FLIN using only word-level and character-level semantic similarity for parameter value scoring (no lexical similarity).

3. **FLIN-lex**: a variant of FLIN using only lexical similarity in parameter value scoring.

4. **FLIN**: Our proposed model described in §4.

### Evaluation Metrics

We use accuracy (\textit{A-acc}) to evaluate action prediction and average F1 score (\textit{P-F1}) to evaluate parameter prediction performance. P-F1 is computed using the average \textit{parameter precision} and average \textit{parameter recall} over test commands. Given a test command, \textit{parameter precision} is computed as the fraction of parameters in the predicted instruction which are correct and \textit{parameter recall} as the fraction of parameters in gold instruction which are predicted correctly. If the predicted action is incorrect, we consider both parameter precision and recall to be 0. We also compute (i) \textit{Exact Match Accuracy} (\textit{EMA}), defined as the percentage of test commands where the predicted instruction exactly matches the gold navigation instruction, and (ii) \textit{100% Precision Accuracy} (\textit{PA-100}), defined as the percentage of test commands for which the parameter precision is 1.0 and the predicted action is correct, but parameter recall \(\leq 1.0\). EMA evaluates how often the model is able to \textit{fully} map the command into the

| Website (Domain) | # Pag | # Act | # Par | Train / Valid / Test |
|------------------|-------|-------|-------|----------------------|
| opentable.com (R)| 8     | 26    | 38    | 14332 / 2865 / 1911  |
| yelp.com (R)     | 8     | 14    | 25    | 1 / - / 993          |
| bookatable.co.uk (R)| 7   | 14    | 19    | - / - / 587          |
| hotels.com (H)   | 7     | 25    | 46    | 15693 / 3137 / 1240  |
| hyatt.com (H)    | 8     | 17    | 48    | - / - / 1150         |
| radissonhotels.com (H)| 7  | 20    | 42    | - / - / 1104         |
| rei.com (S)      | 11    | 25    | 40    | 7001 / 1399 / 933    |
| ebay.com (S)     | 9     | 24    | 38    | - / - / 556          |
| macys.com (S)    | 11    | 26    | 37    | - / - / 619          |
Table 2: In-website and cross-website performance comparison of FLIN variants. The Nav-Dataset is used for training and/or testing, as specified. All metric scores are scaled out of 1.0.

|        | A-acc | P-F1 | EMA  | PA-100 | A-acc | P-F1 | EMA  | PA-100 |
|--------|-------|------|------|--------|-------|------|------|--------|
| R: opentable.com (training website) | FLIN-embed | 0.753 | 0.564 | 0.383 | 0.450 | FLIN-sem | 0.911 | 0.492 | 0.269 | 0.350 |
|        | FLIN-lex | 0.680 | 0.525 | 0.251 | 0.635 | FLIN | 0.970 | 0.820 | 0.681 | 0.730 |
| R: yelp.com |
|        | FLIN-embed | 0.853 | 0.592 | 0.414 | 0.477 | FLIN-sem | 0.923 | 0.391 | 0.230 | 0.338 |
|        | FLIN-lex | 0.784 | 0.663 | 0.364 | 0.773 | FLIN | 0.913 | 0.826 | 0.702 | 0.797 |
| R: bookatable.co.uk |
|        | FLIN-embed | 0.931 | 0.505 | 0.372 | 0.431 | FLIN-sem | 0.956 | 0.358 | 0.273 | 0.323 |
|        | FLIN-lex | 0.946 | 0.509 | 0.345 | 0.527 | FLIN | 0.962 | 0.755 | 0.659 | 0.695 |
| H: hotels.com (training website) |
|        | FLIN-embed | 0.915 | 0.857 | 0.688 | 0.764 | FLIN-sem | 0.933 | 0.675 | 0.309 | 0.347 |
|        | FLIN-lex | 0.833 | 0.689 | 0.269 | 0.798 | FLIN | 0.937 | 0.881 | 0.652 | 0.884 |
| H: hyatt.com |
|        | FLIN-embed | 0.910 | 0.657 | 0.264 | 0.388 | FLIN-sem | 0.964 | 0.594 | 0.155 | 0.281 |
|        | FLIN-lex | 0.825 | 0.555 | 0.120 | 0.621 | FLIN | 0.967 | 0.749 | 0.266 | 0.765 |
| H: radissonhotels.com |
| S: rei.com (training website) |
|        | FLIN-embed | 0.915 | 0.857 | 0.688 | 0.764 | FLIN-sem | 0.933 | 0.675 | 0.309 | 0.347 |
|        | FLIN-lex | 0.833 | 0.689 | 0.269 | 0.798 | FLIN | 0.937 | 0.881 | 0.652 | 0.884 |
| S: ebay.com |
|        | FLIN-embed | 0.925 | 0.700 | 0.296 | 0.376 | FLIN-sem | 0.968 | 0.435 | 0.292 | 0.365 |
|        | FLIN-lex | 0.967 | 0.776 | 0.290 | 0.475 | FLIN | 0.994 | 0.684 | 0.186 | 0.418 |
| S: macys.com |

gold navigation instruction and PA-100 how often it generates correct (i.e., no wrong predictions), but incomplete navigation instructions.

Although we formulate the mapping problem as a ranking one, we do not consider standard metrics such as mean average precision (MAP) or normalized discounted cumulative gain (NDCG) because FLIN outputs only one navigation instruction (with highest relevance score) instead of a ranked list, given that in a real NL-guided web navigation system only one predicted action can be executed.

5.2 Performance Results

Table 2 reports the performance comparison of FLIN on the Nav-Dataset (Table 1). We evaluate both in-website (model trained and tested on the same website, 2-5 columns) and cross-website (model trained on one site and tested on a different one, 6-13 columns) performance. The proposed model (FLIN in the table) and its other 3 variants adapt relatively well to previously-unseen websites thanks to FLIN’s match-based semantic parsing approach. FLIN achieves best overall performance, and is able to adapt to new websites by achieving comparable (or higher) action accuracy (A-acc) and parameter F1 (P-F1) score. Considering PA-100, in the Restaurants domain, 73.0% of commands in the training website (OpenTable) and 69.5% (bookatable) , 79.7% (yelp) of commands in the two test websites are mapped into correct and executable actions (no wrong predictions). PA-100 is generally high also for the other two domains. EMA is lower than PA-100, as it is much harder to predict all parameter value assignments correctly.

Table 3: Performance on the Diag-dataset (models trained on the Nav-Dataset).

|        | A-acc | P-F1 | EMA  | PA-100 |
|--------|-------|------|------|--------|
| opentable.com (R) | 0.837 | 0.712 | 0.692 | 0.709 |
| hotels.com (H) | 0.991 | 0.770 | 0.589 | 0.732 |
| rei.com (S) | 0.727 | 0.664 | 0.613 | 0.659 |

From a scalability point of view, the most challenging domain is Shopping. While in the Restaurants and Hotels domains, FLIN must deal with actions/parameters that relate to the same entity type (restaurants or hotels) with a relatively-contained vocabulary, shopping products can range so widely to be effectively different entity types with a diverse set of actions/parameters that can vary significantly across websites (more in §5.3).

Regarding the FLIN variants, FLIN-embed only learns the embedding of words and averages the embedding vectors to learn the overall semantics. Its performance is sometimes slightly better than FLIN, but mainly for in-website evaluation. Due to its simplistic semantics learning, the model cannot adapt to new websites as well as FLIN. Both FLIN-sem and FLIN-lex perform worse than FLIN because by combining both lexical and semantic similarity FLIN can be more accurate in doing parameter value assignments and generalize better.

We also test FLIN on the real user queries of the Diag-dataset available for three websites sites. As Table 3 shows, despite FLIN not being trained on the Diag-dataset, overall, its EMA is above 58% and its PA-100 is above 65% which demonstrate the
Table 4: Error analysis based on 135 test commands from the Nav-Dataset on which FLIN failed. Columns do not sum up to 100% as multiple parameters in the same command may be problematic for different reasons.

| Error Type                          | % (R) | % (H) | % (S) | % (all) |
|-------------------------------------|-------|-------|-------|---------|
| Action not predicted                | 17.7  | 8.9   | 13.3  | 13.3    |
| Action miss-predicted               | 17.7  | 28.8  | 40.0  | 28.9    |
| Fail to identify closed-domain parameter | 20.0  | 57.7  | 31.1  | 36.3    |
| Closed-domain parameter value miss-predicted | 31.1  | 6.7   | 4.4   | 14.1    |
| Fail to extract open-domain parameter value | 15.5  | 11.1  | 24.4  | 17.0    |

To scale to many websites, NL-guided web navigation assistants require an NL interface that can work with new website UIs without requiring being constantly re-trained from scratch. To achieve this goal we proposed FLIN, a matching-based semantic parsing approach that maps user commands to concept-level actions. So far we have used FLIN in restaurant, shopping and hotels websites, but its approach can apply to many more domains. While various optimizations are possible, FLIN was able to adapt to previously-unseen websites and deliver good performance.

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