Facilitating Conversational Interaction in Natural Language Interfaces for Visualization

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Abstract
Natural language (NL) toolkits enable visualization developers, who may not have a background in natural language processing (NLP), to create natural language interfaces (NLIs) for end-users to flexibly specify and interact with visualizations. However, these toolkits currently only support one-off utterances, with minimal capability to facilitate a multi-turn dialog between the user and the system. Developing NLIs with such conversational interaction capabilities remains a challenging task, requiring implementations of low-level NLP techniques to process a new query as an intent to follow-up on an older query. We extend an existing Python-based toolkit, NL4DV, that processes an NL query about a tabular dataset and returns an analytic specification containing data attributes, analytic tasks, and relevant visualizations, modeled as a JSON object. Specifically, NL4DV now enables developers to facilitate multiple simultaneous conversations about a dataset and resolve associated ambiguities, augmenting new conversational information into the output JSON object. We demonstrate these capabilities through three examples: (1) an NLI to learn aspects of the Vega-Lite grammar, (2) a mind mapping application to create free-flowing conversations, and (3) a chatbot to answer questions and resolve ambiguities.

Index Terms: Human-centered computing—Visualization—Visualization systems and tools—Visualization toolkits; Human-centered computing—Visualization—Visualization tools and techniques—Text input

1 Introduction and Background
Natural language interfaces (NLIs) for databases [5, 13, 14, 21, 28, 31, 44, 49] and visualizations [4, 10, 16, 18–20, 27, 29, 35–38, 41–43, 47] have shown great promise, democratizing access to data through the querying power and expressivity of natural language (NL). Given a dataset (e.g., movies), an NLI for visualization receives an NL query (e.g., “Show the distribution of budget”) as input, extracts data attributes (Production Budget) and analytic tasks (Distribution), and recommends one or more relevant visualizations (Histogram). Many of these NLIs also help resolve ambiguities that may occur during query interpretation. For example, DataTone [10] presents ambiguities through interactive GUI-based widgets (e.g., dropdowns) for disambiguation. Implementing such NLIs, however, requires experience with natural language processing (NLP) techniques and toolkits (e.g., NLTK [23], spaCy [15]) as well as GUI and visualization design tools (e.g., D3.js [6], Vega-Lite [33]), making it challenging for developers without the necessary skillset.

Recently, NL toolkits [9, 22, 25, 29] have enabled visualization developers, who may not have a background in NLP, to create new visualization NLIs or incorporate NL input within their existing systems. For example, given a tabular dataset and an NL query about the dataset, NL4DV generates an analytic specification comprising data attributes, analytic tasks (based on [2]), and visualizations (as Vega-Lite specifications [33]) modeled as a JSON object. However, these toolkits currently support one-off utterances (singleton queries) only, with minimal capability to facilitate a multi-turn dialog between the end-user and the system, e.g., by following-up on a previous query. Because of this, end-users would have to specify longer NL queries (e.g., “Show the relationship between budget and rating for Action and Adventure movies that grossed over 100M”) to accomplish more complex tasks. These types of queries may also have a greater chance of failing (e.g., attribute detection can fail; filter operators may be incorrect), eventually warranting several paraphrasing attempts. We believe specifying multiple short queries in a natural sequence can enable end-users to incrementally accomplish a complex task, fix minor errors, and also make debugging easier, as in [3, 11, 16, 35, 38, 40]. This is called conversational interaction—“face-to-face or technology-mediated forms of interaction that use language, encompassing a wide range of different types of talk” [12].

Developing NLIs with such conversational interaction capabilities remains a challenging task, however, requiring implementations of low-level NLP techniques to process a new query as an intent to follow-up on an older query, e.g., replacing an existing attribute with a new one. To the best of our knowledge, no NL toolkit facilitates conversational interaction, yet. Hence, in this work, we extend a Python-based toolkit, NL4DV [29], in order to enable visualization developers to facilitate multiple simultaneous conversations (through manual specification as well as automatic detection of intents to follow-up) and resolve associated ambiguities through an easy-to-use application programming interface (API). As a result, NL4DV also augments additional conversational information into the output JSON. We demonstrate these capabilities through three examples: (1) an NLI to learn aspects of Vega-Lite – an implementation of a grammar for interactive graphics [33], (2) a mind mapping application to create free-flowing conversations about a dataset, and (3) a chatbot to answer questions and resolve ambiguities in collaboration with the enduser. To support development of future systems, we open-source NL4DV and the described applications at https://n14dv.github.io/nl4dv/.

2 Conversational Interaction with NL4DV
Listing 1 illustrates the basic Python code for developers to enable conversational interaction in their own applications using NL4DV. Given a tabular dataset on Houses (adapted from [7]; accessible at [17]) and a query string specified by the end-user, “Show average prices for different home types over the years”, with a single function call analyze_query(query) (lines 1–3), NL4DV first determines it as a standalone query (as it is the very first query), extracts data attributes and analytic tasks, recommends visualizations, and then assigns new objects that identify that conversation (dialogId = "0") and the corresponding query (queryId = "0") as part of the output JSON (lines 4–5). After observing the output visualization, if the end-user wants a bar chart instead of a line chart, they may ask, “As a bar chart” with a new parameter, dialog = “auto”. NL4DV automatically
Listing 1: Python code illustrating how developers can enable conversational interaction in their applications using NL4DV.

determines this as a follow-up to the previous query (with a heuristically determined followUpConfidence = high) and directly modifies its analytic specification, retaining the dialogId = 0" but generating a new, now incremented queryId = 1" as the second query in the conversation (lines 6-8). If the end-user is suddenly curious about how house prices compare with area, they may ask, "Correlate price and area", explicitly specifying the query as standalone (dialog = False). This time, NL4DV increments dialogId = 1" and resets queryId = 0" since this is now the first query of a new, second conversation (lines 9-11). If the end-user wants to resume their original conversation and only focus on certain home types, they may ask, "Just show condos and duplexes", time explicitly specifying the query as a follow-up (dialog = True, dialogId = 0") with additional parameters: dialogId = 0", queryId = 1", that correspond to the first conversation (lines 12-14). As expected, the resultant dialogId = 0" and queryId = 2", along with the filtered bar chart.

To achieve this kind of conversational interaction, we extended NL4DV [29]; Figure 1 illustrates the modified technical architecture. The existing Query Processor module parses the input NL query using NLP techniques such as tokenizing and parts of speech tagging (Query Parser), extracts data attributes through semantic and syntactic similarity matching (Attribute Identifier) and analytic tasks through dependency parsing (Tasks Identifier), and recommends relevant visualizations based on heuristics used in prior systems [26,45,46] (Visualization Specification Generator), that are

```python
from nl4dv import NL4DV
nl4dv_instance = NL4DV(data_url="housing.csv")
resp_1 = nl4dv_instance.analyze_query("Show average prices for different home types over the years.")
print(resp_1)
# a new dialogId and a queryId get created.
{
    "dialogId": "0",
    "queryId": "0",
}

# this query is automatically inferred as a follow-up.
resp_2 = nl4dv_instance.analyze_query("As a bar chart.", dialog=auto)
print(resp_2)
{
    "dialogId": "0",
    "queryId": "1",
    "followUpConfidence": "high",
}

# this query is a new, standalone query.
resp_3 = nl4dv_instance.analyze_query("Correlate Price and Lot Area.", dialog=False)
print(resp_3)
{
    "dialogId": "1",
    "queryId": "0",
}

# this query follows up a specific, older query.
resp_4 = nl4dv_instance.analyze_query("Just show condos and duplexes.", dialog=True, dialog_id="0", query_id="1")
print(resp_4)
{
    "dialogId": "0",
    "queryId": "2",
}
```

Figure 1: Original NL4DV architecture [29] (in gray) extended to support conversational interaction (in orange). The arrows indicate the flow of information between the modules.

Listing 2: Data structure to store multiple conversations, including branches (multiple follow-ups to the same query).

combined into an Output JSON. The new Conversation Manager module enables developers to automatically determine or manually specify a query as a follow-up (or not). This module also determines the type of follow-up (e.g., add or remove attributes), managing all operations on the internal data structures. Also new, the Query Resolver module facilitates resolving NL ambiguities (e.g., by “medals” did the end-user mean “{Total | Gold | Silver | Bronze | Medals?”).

2.1 Facilitating Multiple Simultaneous Conversations

Following the dialog shown in Listing 1, whenever the end-user asks a new, standalone query, the dialogId is also incremented by “1" and the queryId is re-initialized to “0" (identifiers are stringified after incrementing for efficient handling of data), creating a new dialog instance that is uniquely identifiable by dialogId and queryId. Subsequently, developers can explicitly follow up on specific queries by passing the follow-up query string along with additional input parameters: dialog (a boolean flag expressing an explicit intent to follow-up), dialogId, and queryId to analyze_query(query).

This design also enables end-users to ask multiple unrelated follow-ups to the same query. To create such conversational branches, developers can provide the same dialogId and queryId in repeated calls to analyze_query(query). Internally, NL4DV creates the desired branch point and outputs a new, unique dialogId with the format: "{dialogId}, {queryId}, {branchId}" (similar to the semantic versioning format [34]), where {branchId} is the index of the branch stemming from the input parameters: {dialogId} and {queryId}. This naming convention effectively represents the hierarchy of all entities involved in the conversation. Listing 2 shows how NL4DV stores these conversations in a Python dictionary of lists with dialogId as the keys and queryIds as the indexes of the corresponding list of queries. This data structure enables efficient retrieve, append, modify, and delete operations. Note that calling analyze_query(query, dialog=True), without dialogId or queryId, will make NL4DV follow up on the most recent dialogId and queryId; if these too do not exist (e.g., it is the very first conversation), then an error is thrown.

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2.2 Detecting, Classifying and Processing Follow-ups

To supply dialog, dialog.id and query.id parameters to analyze_query(query), developers have to provide GUI affordances for end-users, e.g., a checkbox to specify if dialog=True or not (and which conversation to follow-up on), which can be an unnatural end-user experience. To alleviate this, NL4DV offers a dialog=True setting (overloading the otherwise boolean input data type) that automatically determines if the query is a follow-up or not and outputs a followUpConfidence rating: {"high", "low", "none"} reflecting NL4DV’s confidence in making the inference. This rating is heuristically determined based on the previous query, an explicit_followup_keywords map — keywords that convey natural conversational intents to follow-up (e.g., “add”, “replace”), and an implicit_followup_keywords map — keywords that implicitly convey an intent to follow-up (e.g., “instead of”, “only”). The implicit_followup_keywords are further classified as non-ambiguous — keywords that always convey an intent to follow-up (e.g. “instead of”, “rather than”) and ambiguous — keywords that can occur in a follow-up as well as a standalone context (e.g. “only”). NL4DV assigns queries keywords, or explicit and ambiguous keywords with a high followUpConfidence rating and implicit ambiguous keywords with a low followUpConfidence rating. For queries with no matching keywords, NL4DV compares the attributes, tasks, and visualizations of the current and the previous query and based on a heuristics and rule-based decision tree, assigns either a low or none followUpConfidence rating, the latter corresponding to a new, standalone query. For example, a query “Show the average now.” is a compatible follow-up to its predecessor, “Show maximum price across different home types.”; the desired change from “maximum” to “average” is in the absence of any other follow-up keywords or attributes makes them compatible. Developers can override these default maps by supplying custom explicit_followup_keywords and implicit_followup_keywords objects through the NL4DV constructor during initialization.

Next, the explicit_followup_keywords map classifies the follow-up query as one of three types: add, remove, or replace (inspired by Evizeon’s continue, retain, shift transitional states [16]) and maps it to one or more components of an analytic specification: data attributes, analytic tasks, and visualizations. Note that the resultant combinations (e.g., replace + data attribute) are not always mutually exclusive, e.g., replacing an attribute can sometimes also modify the task(s) and/or the visualization(s). Lastly, NL4DV references the parent query’s (the query being followed upon) analytic specification and makes necessary associations (e.g., creating new conversational branches) and modifications (e.g., dropping an existing attribute), eventually generating a new specification as a JSON object.

By configuring the keyword maps and supplying methods with appropriate parameters, end-users can add, remove, or replace data attributes, either explicitly, e.g., “Replace budget with gross” — which makes a direct reference to the data attributes and the follow-up task; or implicitly, e.g., “Now show only budget” — which indirectly suggests to remove all other attributes except “Production Budget”. Unlike attributes containing follow-up tasks is different because end-users are unaware of the associated technical jargon, e.g., “Add Find Extremum to Worldwide Gross” is not a natural query an end-user would ask; they would rather say, “Show me the highest grossing Extremum to Worldwide Gross”.

This rating is heuristically determined based on the previous query, and based on a heuristics and rule-based decision tree, assigns either a low or none followUpConfidence rating. For queries with no matching keywords, NL4DV compares the attributes, tasks, and visualizations of the current and the previous query and based on a heuristics and rule-based decision tree, assigns either a low or none followUpConfidence rating, the latter corresponding to a new, standalone query. For example, a query “Show the average now.” is a compatible follow-up to its predecessor, “Show maximum price across different home types.”; the desired change from “maximum” to “average” is in the absence of any other follow-up keywords or attributes makes them compatible. Developers can override these default maps by supplying custom explicit_followup_keywords and implicit_followup_keywords objects through the NL4DV constructor during initialization.

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Vega-Lite filters are specified. To develop this interface, developers can call **analyze_query**(query, dialog, dialogId, queryId), supplying the dialog and query identifiers based on the corresponding query that is to be followed-up. Then, based on the newly generated dialogId and queryId, a new node is created and appended to the corresponding predecessor query node.

### 3.3 Collaboratively Resolve Ambiguities in a ChatBot

In this third use-case, we demonstrate how NL4DV’s **Query Resolver** can help resolve ambiguities that often occur in natural language. Figure 4 illustrates a standard chatbot user interface that presents DataTone-like [10] “ambiguity widgets”—drop-downs and buttons. End-users can disambiguate by interacting with the widgets, notifying NL4DV through a function call to **update_query**(obj). After all ambiguities are resolved, the system renders the unambiguous visualization. To develop this interface, developers can loop through the **ambiguities** object in the output JSON and present corresponding **options** to the end-user, e.g., as options in a select dropdown. As the end-user makes their choices, a function call to **update_query**(obj) will resolve the ambiguity, updating the **selected** properties in the output JSON. Listing 3 illustrates this data exchange between the user interface and NL4DV.

### 4. Conclusion, Limitations, and Future Work

In this work, we extend an existing natural language (NL) for data visualization toolkit, NL4DV, to enable developers to integrate conversational interaction capabilities within natural language interfaces. We demonstrate NL4DV’s capabilities through three examples and open-source the toolkit at [https://nl4dv.github.io/nl4dv/](https://nl4dv.github.io/nl4dv/).

While testing, we noted certain conversational ambiguities, e.g., if a query, “Show only R-rated movies” is followed-up with “What about R-rated movies?”, the user means to augment the previous filter or replace it with the new one? Consider another query, “Visualize budget distribution as a histogram instead of a boxplot” here, the user means to ask a standalone query, but the presence of “instead of” (an implicit follow-up keyword) will make NL4DV wrongly treat it as a follow-up. We will address these ambiguities and translation errors in future releases. We also plan a formal performance evaluation of the toolkit. However, unlike conversational text-to-SQL dataset benchmarks (e.g., CoSQL [48]), there are currently no such benchmarks for visualization tasks. An area of future work, thus, for current text-to-visualization datasets [9, 24, 39], that focus on singleton utterances, is to include multi-turn utterances.

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