AI Magazine Volume 23 Number 2 (2002) (© AAAI)



# Natural Language Assistant

## A Dialog System for Online Product Recommendation

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■ With the emergence of electronic-commerce systems, successful information access on electronic-commerce web sites becomes essential. Menu-driven navigation and keyword search currently provided by most commercial sites have considerable limitations because they tend to overwhelm and frustrate users with lengthy, rigid, and ineffective interactions. To provide an efficient solution for information access, we have built the NATURAL LANGUAGE ASSISTANT (NLA), a web-based natural language dialog system to help users find relevant products on electronic-commerce sites. The system brings together technologies in natural language processing and human-computer interaction to create a faster and more intuitive way of interacting with web sites. By combining statistical parsing techniques with traditional AI rule-based technology, we have created a dialog system that accommodates both customer needs and business requirements. The system is currently embedded in an application for recommending laptops and was deployed as a pilot on IBM's web site.

For electronic-commerce web sites, enabling fast access to product information is crucial for generating sales. Users (customers) need to find products matching their interests, and businesses need to organize product information to permit quick access. Menu-driven navigation provided by most commercial sites have tremendous limitations because they tend to overwhelm and frustrate users with lengthy and rigid interactions. User interest in a particular site decreases exponentially with the increase in the number of mouse clicks (Huberman et al. 1998). Hence, shortening the interaction path to provide useful information becomes important.

Many electronic-commerce sites attempt to solve the problem by providing keyword search capabilities. However, keyword search engines usually require that users know domain-specific jargon so that the keywords could possibly match indexing terms used in the product catalog or documents. Keyword search does not allow users to precisely describe their intentions or specify relational operators (for example, less than, cheapest) on product attributes. A search for *shirt* can reveal dozens or even hundreds of items, which are useless for somebody who has a specific style and pattern in mind. Moreover, keyword search systems lack an understanding of the semantic meaning of the search words and phrases. For example, keyword search systems usually cannot understand that *summer dress* should be looked up in women's clothing under *dress,* whereas *dress shirt* is most likely in men's under *shirt*. Finally, search engines do not accommodate business rules, for example, a prohibition against displaying cheap earrings with more expensive ones.

A solution to these problems lies, in our opinion, in centering electronic-commerce web sites on natural language (and multimodal) dialog. Dialog allows the user and the machine to jointly arrive at the intended meaning of the query. Because it is a joint effort, the process is fast. Moreover, it is natural for the site owner to implement business rules as part of the dialog pragmatics. Based on these ideas, we have built the NATURAL LANGUAGE ASSIS-

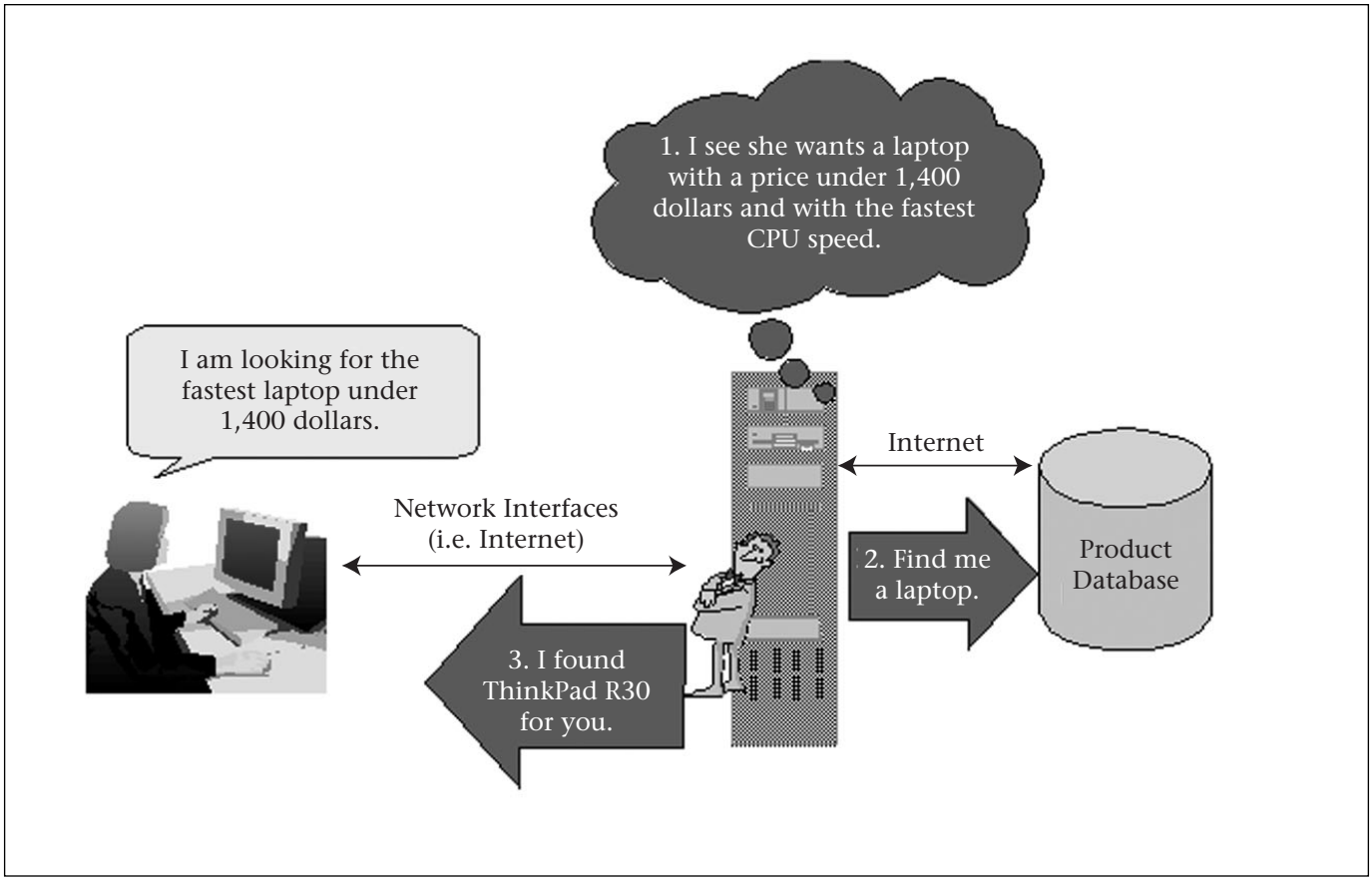


*Figure 1. Interacting with NLA.*

TANT (NLA), a web-based natural language dialog system to help users find relevant products on electronic-commerce sites.

Even though natural language dialog has been used in many domains, and different architectures are designed for supporting such systems (for example, Allen, Ferguson, and Stent [2001]), there is no general and practical theory of engineering such applications. NLA is therefore another case study, following recent applications that include call-center routing (Chu-Carroll and Carpenter 1998), e-mail routing (Walker, Fromer, and Narayanan 1998), information retrieval and database access (Androutsopoulos and Ritchie 1995), and telephone banking (Zadrozny et al. 1998).

NLA allows customers to make requests in natural language and directs them toward appropriate web pages that sell IBM laptops. The system applies natural language understanding to interpret user input, engages in a follow-up dialog with users to provide explanations and to ask for additional information, and makes recommendations. The required tight integration of natural language dialog with an electronic-commerce environment is a novel feature of our system. This work involves engineering dialog for presenting the merchandise to the user, using user interface studies to guide both the form and the content, and designing the system to support business rules and business processes for updating the data (for example, when offerings change). NLA was deployed in a pilot study at an IBM external web site. The data we collected, together with appropriate business requirements, will form a basis for a decision about its possible wider deployment. The goal of this article is to describe the behavior and the architecture of the system together with the lessons learned.

In this article, we start with a typical user session with NLA. We then give a detailed description on the general architecture and NLA components. Finally, we present the evolution of the system, showing how results from the user studies shaped the development.

## Interacting with NLA

When searching electronic-commerce sites, users often have target products in mind but do not know where to find information or how

to specify a request. Sometimes, users only have vague ideas about the products of interest (Saito and Ohmura 1998). Thus, users need to be able to formulate their requests in their own words as well as revise their request incrementally based on additional information, which can be provided through natural language dialog. NLA was built with that in mind.

Figure 1 shows a high-level view of NLA. Users specify their needs to NLA in their own words over the internet. NLA interprets the input, retrieves products, and gives its response to the user. For example, when the user specifies the *fastest computer under $1400*, based on the understanding of this input, NLA retrieves the laptop (a ThinkPad R30 model) that has the fastest central processing unit (CPU) speed among all laptops with a price less than $1400. This example demonstrates the tremendous advantage of natural language search because the user is able to obtain the desired product in one interaction rather than navigate up and down several layers of menus (menu-driven navigation) or browse among several irrelevant pages (keyword search). A keyword search system can result in no hit or too many hits because the relational operators specified by *fastest* and *under $1400* are typically neither identified nor computed by search engines. Furthermore, in a menu-driven navigation, the user might not be able to choose the product that has the fastest CPU speed within the price range if he/she has no knowledge that it is the CPU speed that determines whether a computer is fast or not.

In addition to the capability of finding products in one click, NLA also engages users in a dialog to elicit their needs and provide guidance. Figure 2 shows a typical user session with NLA. Note that the user can describe his/her requirements using either specifications on product attributes (Memory in utterance User[1], Operating System and Battery life in User[2]), or general concepts (User[4]). Furthermore, the user can express multiple constraints in one input (User[2], User[3]). In this example, NLA explains to the user why a certain requirement cannot be satisfied (NLA[2]) and helps the user narrow down the search space (NLA[3], NLA[4]). NLA does not force the user to only answer the specific questions put to them. For example, NLA asks the user about the price constraints (NLA[2], NLA[4]); however, the user bypasses this question and provides additional criteria (figure 3). This type of "mixed-initiative" interaction provides flexibility to the user in specifying his/her needs and NLA in guiding the user (figure 4).

NLA [1]: What type of ThinkPad are you looking for?

User [1]: *"Something with at least 256 mb ram."*

NLA [2]: ThinkPads ship with memory between 64 and 128 MB. I could not find any ThinkPads. Here are some popular modules. What are your price constraints? (figure 3)

User [2]: [presses Start Over button] *"A windows 2000 computer with a battery life of at least 3 hours."*

NLA [3]: I found 18 ThinkPads for you. What are your speed and RAM requirements?

User [3]: *"At least 128 mb ram with multimedia features."*

NLA [4]: I found 2 ThinkPads for you. What are your price constraints?

User [4]: *"The lightest one."*

NLA [5]: I recommend the ThinkPad model T23 for you. (figure 4)

*Figure 2. Example Scenario.*

## System Overview

Our architecture (figure 5) is designed to support mixed-initiative dialog with multiple modalities, including typed-in text and speech. We use a hub-and-spokes architecture with a central hub responsible for shuttling messages between all other components.

The user interface module is responsible for receiving user input and presenting system output. Once the input is received by the hub, the shallow parser parses it and captures important expressions that are used to describe certain features of ThinkPads (for example, hard-disk size, CPU speed) or the usage patterns (for example, for travel). Based on these expressions and the session context maintained by the dialog manager, the interpreter constructs a set of constraints on attributes of ThinkPads. These constraints are then translated to an SQL query by the action manager. The action manager executes the SQL query against a relational product database and retrieves a set of products matching user constraints. Based on the identified constraints and the retrieved products, the dialog manager constructs different responses such as requesting clarification and soliciting more information to narrow the recommendation list. Finally, the user interface

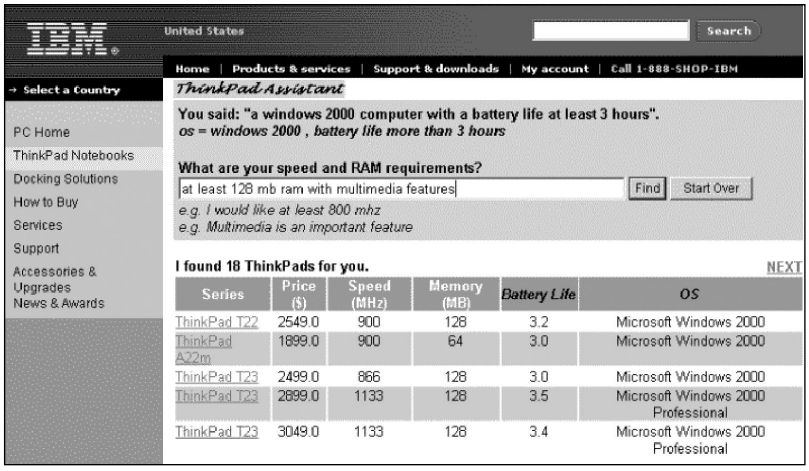


*Figure 3. A Screenshot of NLA User Interface for Requesting More Information.*

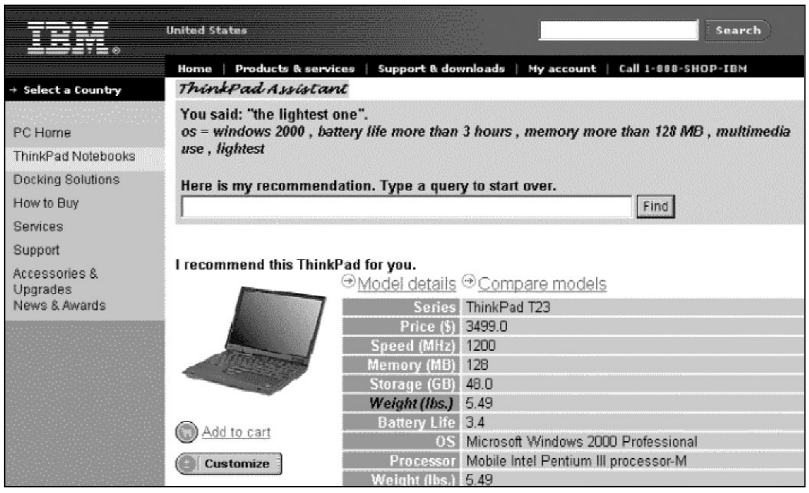


*Figure 4. A Screenshot of NLA Interface for Final Recommendation.*

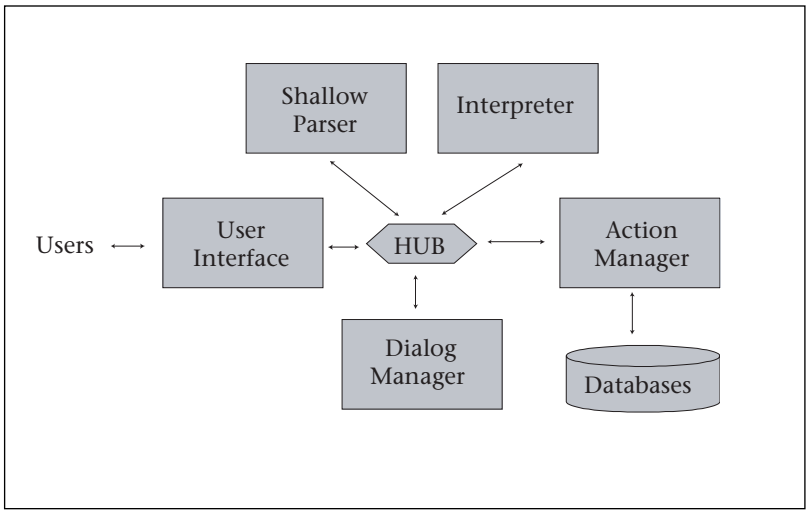


*Figure 5. General Architecture.*

module renders a screen presenting these responses and the retrieved products to the user. From this interface, the user can start another interaction with NLA. We now describe each of these components in details.

## User Interface Module

The *user interface module* is responsible for receiving user input and displaying system output. In our architecture, we have a separate user interface for each modality of interaction. The dialog manager determines the content of what is to be presented, and the specific user interface renders it using the unique capabilities of the channel or modality of interaction.

For the web-based interaction, we designed the NLA interface to have a consistent look and feel in every screen. For example, the dialog box is positioned at exactly the same place on every screen. Furthermore, in every screen, NLA reiterates the user input and provides feedback on what constraints have been understood to this point. Such feedback is also reflected in the table of products, where NLA dynamically highlights the attributes in the column that correspond to the identified constraints.

Figure 3 shows a screenshot of the user interface for NLA [3] in figure 2. Note the follow-up question is shown to the user to solicit more information for the purpose of narrowing the retrieved product list. Furthermore, both *battery life* and *OS* are highlighted in the product table to reflect the user-specific requests. Figure 4 shows a screenshot of the user interface for the final turn (NLA [5]) of the dialog session in figure 2. Note the merged constraints from previous turns are shown at the top of the page as a feedback.

## Parser

NLA uses a shallow *statistical parser* to identify expressions in a user input referring to product specifications (for example, CPU speed, harddisk capacity) or usage categories (for example, for multimedia applications). Using a statistical approach allows us to scale to multiple languages and geographies with minimal reconfiguration. Thus, to create a French language version of NLA, we would only need to collect a corpus of French sentences and annotate them with the existing schemes, instead of recruiting French-speaking linguists to create rules for French expressions.

Specifically, the statistical parser learns decision tree models using a corpus of sentences annotated with parse trees. The parser then applies the learned models on user input to create semantic parse trees in a bottom-up, leftmost order (Magerman 1995; Magerman et al.

1994). The parse trees are relatively shallow in our domain given the brevity of user input. For example, given the input *at least 128mb with multimedia features*, the parser will generate the most-probable parse tree, as shown in figure 6, together with the probability for this tree. In this parse tree, the nonterminals (for example, random-access memory [RAM], multimedia) are labels that capture the semantic categories of the user input, and the terminals (for example, at least 128 megabytes) are the actual user expressions. This resulting parse tree is used by the interpreter to extract constraints. The parser is robust and fast and is not memory intensive. It is packaged as a separate module and receives parse requests using socket communication.

During the development, we collected 10,069 user queries about ThinkPads to build the statistical parser model. We used 6,804 queries as a training set for the parser, 2,253 as a validation set and 1,012 as a test set. The queries were collected from user interactions with a previous version of the system using a finite-state parser (Chai et al. 2001a). We utilized 32 *labels* to categorize different attributes of ThinkPads (for example, *price, weight*) and 6 labels to categorize usage patterns (for example, *travel-use, multimedia*). We have gone through several cycles of revising the initial annotation, fine tuning the parser features, and retraining the model.

Currently, the parser parses the test set with an average precision of 92 percent and an average recall of 94 percent for identifying the labels. In general, the parser works best for labels associated with well-defined crisp semantic meanings (for example, *price, CPU speed*). If we only consider the labels corresponding to product attributes, we obtain an average precision of 94 percent and an average recall of 98 percent for the test set. For labels corresponding to usage categories that tend to be more subjective in nature (for example, *cutting_edge*), we obtain an average precision of 84 percent and an average recall of 80 percent for the test set. Thus, our parser is good at identifying common product attributes but works less well for identifying all possible interpretations of subjective use categories. We believe that training with more data and modifying our label selection and annotation schemes will help with identifying use categories.

## Interpreter

The *interpreter* extracts a semantic representation (for example, propositional formula of constraints over product attributes) from the parse tree returned by the parser. Specifically,

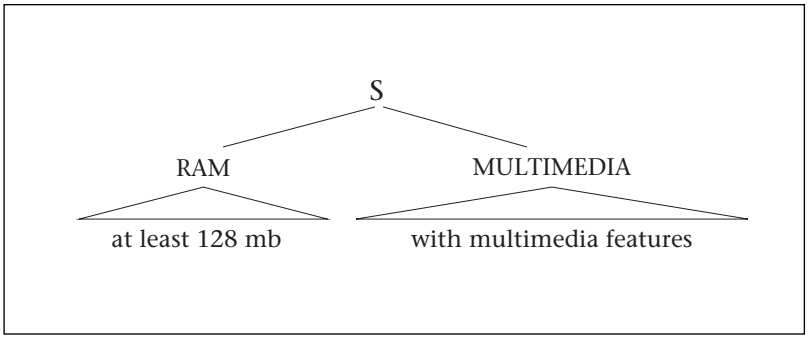


*Figure 6. Parse Tree for the Input "at Least 128 MB with Multimedia Feature."*

from all the labeled chunks of text identified by the parser, the interpreter extracts constraints that specify relations and values for product attributes (for example, *price < 2500, weight = min, CPU type = Pentium*). Furthermore, to keep the context of a dialog, the interpreter also integrates the constraints identified from the current input with the constraints captured previously in the session.

The interpreter first extracts constraints from the labeled chunks of text describing product specification. Depending on the (abstract data) types of the attributes, we distinguish between numeric constraints (*price < 2500*), string constraints (*CPU type = Pentium*), and constraints over pairs (*resolution* = 1600 x 1200). The values of numeric constraints are normalized to canonical units of measure (dollars for *price*, megahertz for *CPU speed*, and so on) using finite-state transducers. For example, given a user expression *faster than 1.3 GHz,* which is categorized as *CPU speed*, the interpreter converts *1.3 GHz* into *1300 MHz*.

We have explored two approaches for the treatment of string-valued attributes. The first approach uses finite-state patterns to produce a canonical string value that is directly matched (for example, using substring matching in SQL) against string values in the product database. This approach requires us to prespecify a canonical list of values for each string-valued product attribute. Thus, this approach requires ongoing system maintenance costs as new products are released with either new values for existing attributes or with new attributes.

To avoid such dependencies on external (to our dialog system) resources, we have implemented an approach using information-retrieval techniques. NLA matches the expression in a particular attribute category with values of that attribute in the product database and chooses the most similar one(s) using similarity measurement. For example, for the query *I want a machine with win xp*, the interpreter identifies the constraint (*OS = win xp*). If

```
MULTIMEDIA ::=      (DEVICE = dvd) &
                    (CPUSPEED: high) &
                    (HDSIZE: high) &
                    (DISPLAY ≥ 14.1).
```

*Figure 7. An Example of a Business Rule.*

```
SELECT * FROM table WHERE
        ram = 256 AND
        price < 2000 AND
        cpuspeed = (SELECT max(speed) FROM table WHERE
                                price < 2000 AND
                                ram = 256).
```

*Figure 8. An Example of an SQL Statement Generated by the Action Manager.*

the values for the OS attribute in the database are *Microsoft Windows XP Professional, Windows NT, Windows 2000 Professional,* and *Linux,* the best match is *Microsoft Windows XP Professional*.

For expressions in the usage category, the interpreter applies business rules to create constraints. Business rules provide a mechanism for bridging the gap between user vocabulary and business requirements. In other words, the parser provides the usage categories identified from the user input, and the business rules specify how these categories relate to products (by providing constraints on product specifications). For example, the multimedia use category is defined by the business rule in figure 7.

The rule in figure 7 indicates that a machine that can be used for multimedia purposes should have a DVD, a high-CPU speed, a large disk drive, and a display with at least 14.1 inches. This example also shows the use of qualitative constraints (for example, *HD size: high*) that are low or high constraints on numeric product attributes. The qualitative constraints are further mapped to specific constraints such as *HD size > 20 GB* based on automatic partitioning of the current range of values. For example, among all available values for the hard-disk size, the top one-fifth are considered high. Using qualitative constraints in business rules can reduce the maintenance effort. For example, the size of a hard disk that is considered large changes with time as larger disk spaces are available in new products. By using qualitative constraints, when such changes occur, the business rule can remain the same, although the constraint (*HD size: high*) will be interpreted differently through a dynamic mapping of *high* to a new range of values.

Constraints are grouped together with the usual propositional connectives to form formulas. Most often, the connectives are conjunctions, and elements in the formulas are either constraints or negated constraints. These formulas are passed to the action manager to retrieve products.

Furthermore, to keep the dialog context, the interpreter merges the constraints identified from the current input with those captured previously in the session. It is possible to have multiple constraints on the same attribute. They could either have been specified directly by the user or could occur because of the expansion of business rules. We use the following heuristics in the integration process. First, constraints directly specified by the user override other constraints. For example, if the user wants a multimedia machine (which implies *CPU speed: high,* which, in turn, is expanded as *CPU speed > 1000*), and the user explicitly requested *CPU speed > 900*, then the resulting constraint from the CPU speed would be *CPU speed > 900*. Second, the most recent constraint overrides previous constraints with the same attribute and relation. For example, if the user had previously specified *Price < 2000* and is now expressing a new constraint (*Price < 1800*), the most recently expressed constraint (*Price < 1800*) will prevail. Third, constraints on the same attribute with different compatible relations are preserved. For example, combining *Price < 2000* from a previous turn with *Price > 1500* results in the range 1500 to 2000; that is, both constraints are kept.

## Action Manager

The *action manager* is responsible for the backend operations. In particular, the action manager translates constraints generated by the interpreter to an SQL statement. Based on this SQL, the dialog manager retrieves products from a relational database that contains product information. For example, if in consecutive turns, the user specifies *256 MB* and *fastest under 2000 dollars,* then the generated SQL is as shown in figure 8.

To process the min-max constraints properly, the dialog manager considers the set of products satisfying the constraints from previous turns and, among these, identifies products satisfying min-max constraints. Furthermore, when multiple min-max constraints are given, the dialog manager first applies all con-

straints other than the min-max constraints and then applies the min-max constraints in reverse order of occurrence. This order of applying constraints is necessary to ensure the retrieved products correspond to the most common linguistic interpretation of min-max constraints. For example, for the query *fastest, lightest computer with 20 GB*, the action manager first searches for *20 GB*; then the *lightest;* and, finally, the *fastest*. That is, of all machines with hard disk of 20 gigabytes, consider those with minimum weight and among those select the fastest. Any other order of processing constraints would correspond to a different interpretation of the user constraints and might result in unintended products being retrieved.

## Dialog Manager

The *dialog manager* generates the system response based on the current user input, the prior dialog in the session, and the retrieved products. In particular, the dialog manager utilizes a mixed-initiative strategy to interact with a user. At the beginning of each session, the dialog manager prompts users with a general question (for example, NLA[1] in figure 2) to solicit specific requests. Moreover, at any point in the session, the dialog manager allows users to bypass questions put to them and describe their needs directly. Although giving the initiative to users, the dialog manager also takes the initiative by asking users very specific questions about different product attributes, thus directing the users to achieve their dialog goals.

NLA differentiates between two types of users. If the user's initial query expresses requirements on any product attributes directly, the dialog manager classifies the user as a *technology savvy* user, and for the remainder of the session, the dialog manager only prompts him/her with questions concerning specific product attributes. Alternatively, if the user's initial query expresses only usage patterns, for the remainder of the session, the dialog manager only prompts the user for information on general uses.

The dialog manager utilizes different strategies to deal with different situations. When no constraints are identified from a user input, the dialog manager presents a clarification screen suggesting possible queries and explaining the capabilities of NLA. When a user specifies an invalid constraint (for example, User[1] in figure 2), the dialog manager presents the valid range of constraints for the attributes in question and prompts the user to reformulate his/her query. If the action manager retrieves more than one product based on constraints identified to this point, the dialog manager prompts the user for constraints on product attributes or usage categories (depending on the first query, as explained earlier) that best discriminate among the retrieved products. If the action manager retrieves exactly one product based on constraints identified to this point, the dialog manager recommends the product to the user, explains the reason for the recommendation, and invites the user to start another search.

In a special situation where constraints identified result in no products being retrieved, the dialog manager uses the following strategy: The dialog manager (by way of the action manager) separately retrieves a pool of products for each constraint. If any of these product pools is empty, the dialog manager prompts the user with the range of values for the corresponding product attribute. The dialog manager then merges (union of sets) all the nonempty product pools and sorts them using a distance measure that measures the closeness of a product to the set of constraints. This merged product pool is presented to the user along with an alert about the conflicting nature of the identified constraints. For example, if the user inputs *under 1000 dollars and at least 900 MHz,* the action manager will not retrieve any products because no laptop satisfies both these constraints. In this case, the dialog manager instructs the action manager to separately retrieve the pool of laptops that are priced under $1000 and the pool of laptops that have at least 900-megahertz CPU speed. These two product pools are merged and sorted with respect to closeness to both the constraints. The sorted list is presented to the user. If all the product pools are empty, the user is prompted to reformulate his/her query.

The dialog manager maintains a dialog history that records the user input, the set of identified constraints, the list of products retrieved, and the system output at each turn of the dialog. Unlike other systems that have complex structures capturing user intentions and the focus of attention (for example, LINLIN [Jonsson 1997]), our dialog history is simple. However, we found that this simple representation is sufficient for our application.

## Data Management and Maintenance

We have developed various tools and processes to maintain the NLA system to ensure that updates to products and other resources are seamlessly reflected in user interactions. In a business setting, various databases are often predesigned for other purposes and, hence, present problems for our system; for example,

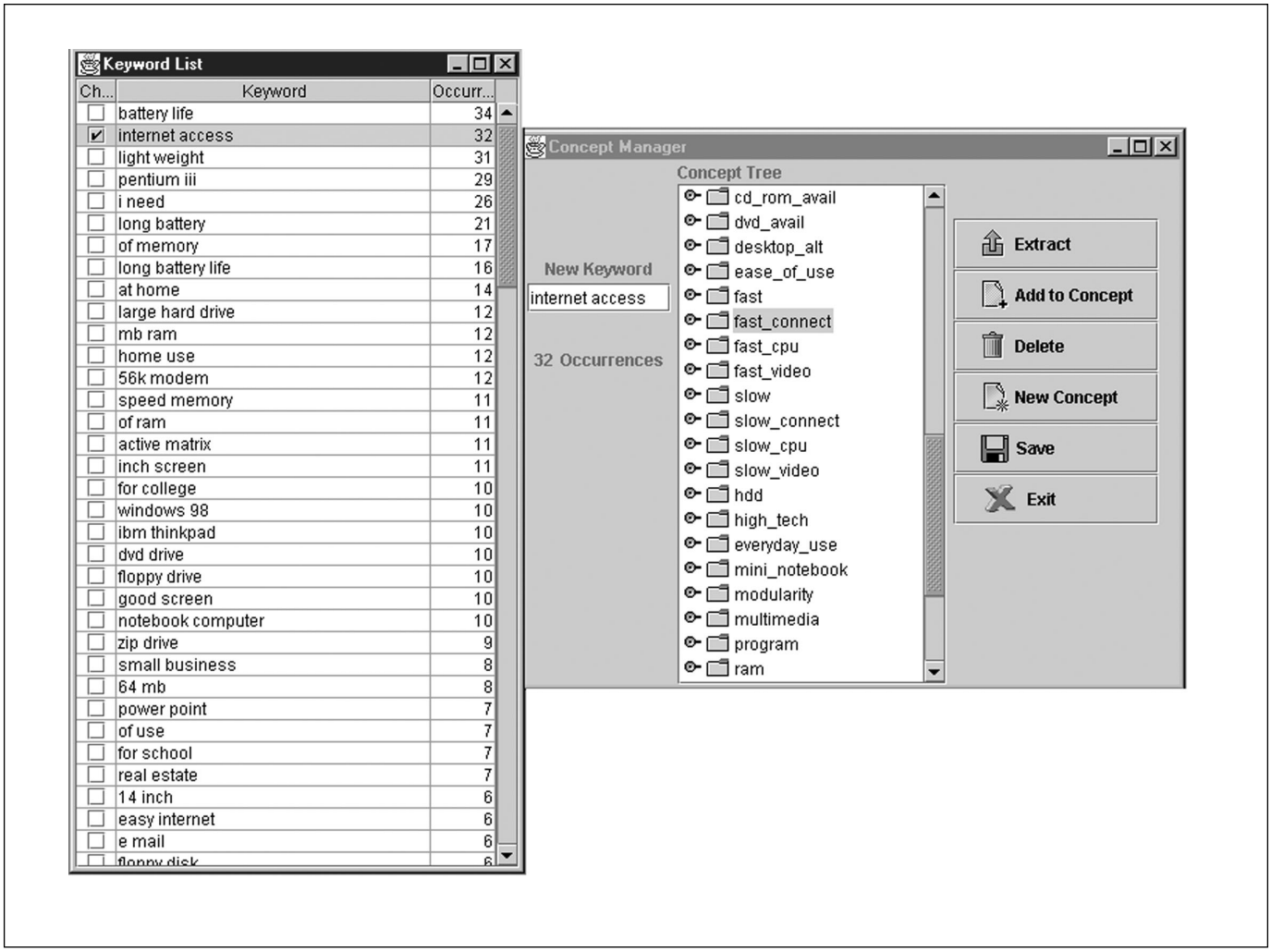


*Figure 9. Editing Interface for Concept Management.*

the database might not have the right data types, or multiple attributes might be represented in a single database column. To address these issues, we maintain a local database that is populated directly from the original databases. We implemented an automated process to access the product databases to convert data types and extract product specification on a daily basis. Our script robustly copes with missing data values, multiple attributes merged into one attribute, and so on. In addition, we have also explored the direct extraction from product web pages using a web-based tool that uses finite-state patterns to extract product specifications.

Furthermore, when new products or features are introduced, the business rules need to be updated accordingly. When more and more user input are collected, the statistical parser needs to be retrained. Thus, we have implemented a tool for maintaining business rules and the statistical parser. The tool automatically extracts *n*-grams from logs of user queries and allows manual updates of business rules through an editing interface. A parts-of-speech tagger and a noun phrase grammar are used to select new input patterns. The new patterns are labeled through the interface and added to the training examples for the statistical parser. Figure 9 shows the interface where automatically identified bi-grams can be added to existing categories.

In addition to coping with the evolving data from the technology aspect, it is worth pointing out that human interaction is important in the data management process. In a business organization, different groups are responsible for different product parameters. Thus, interacting with different groups to understand the structure and the type of the data is important. Such interactions usually take a lot of effort and add the complexity of data management.

## Implementation

NLA is implemented as a client-server system using JAVA servlets, WEBSPHERE, and DB2. We utilize HTTP to communicate between the client and the server. The system development was done under VISUAL AGE for JAVA. The user interfaces were implemented using DHTML (HTML4.0, cascading style sheets, and JAVASCRIPT), JAVA server pages, and JAVA servlets. We have developed versions of NLA for different geographies as well as for different product lines.

For efficiency reasons, the statistical parser is implemented in C. The NLA system connects to the parser with sockets. For training the parser, we preannotated data using a finite-state parser used in a previous version of the system (Chai et al. 2001b). These raw annotations were reviewed manually using a graphic user interface annotation tool. We have also used examples artificially generated using a Prolog definite clause grammar (DCG) to cover more variations in user input.

# System Evolution by Iterative Design

The present version of NLA has evolved through various cycles of iterative design. Specifically, we went through four stages of system development: (1) concept proof, (2) prototyping, (3) pilot deployment, and (4) postpilot enhancement. During these stages, we incrementally designed and implemented different versions of NLA and conducted user studies to evaluate the technology and improve the system. In this section, we share our experience and the results from the user studies carried out at separate stages of development.

## Proof of Concept

For the proof of concept, we developed HAPPY ASSISTANT, a simple rule-based system that provided limited language processing and dialog capabilities (Chai et al. 2001a). At this initial stage of development, it was important to learn users' reactions to this novel navigation approach as opposed to traditional approaches (for example, menu-driven navigation). Thus, we compared HAPPY ASSISTANT with a menu-driven system. We were particularly interested in finding answers to the following questions: Can natural language–based navigation be more efficient (number of clicks, time spent searching, and so on) and easier to use than menu-driven navigation and by how much? What are users' responses toward natural language–based navigation as opposed to menu-driven navigation? How do users with different levels of online experience react to the natural language dialog–based navigation?

| System | Novice | Intermediate | Experienced |
|---|---|---|---|
| HAPPY ASSISTANT | 9.4 | 8.5 | 8.3 |
| Menu-Driven System | 6.3 | 8.1 | 8.9 |

*Table 1. Ratings of Ease of Use of the Two Systems.*

Seventeen subjects were recruited for the comparative study: Four had advanced computer skills, eight were deemed to be at the intermediate level of proficiency, and five had limited experience with the internet. Each participant was asked to use both the HAPPY ASSISTANT and the menu-driven system, following a set of predefined scenarios. The scenarios were designed to let the users experience the navigation of each web site to form an opinion of the tool's concept. They were then asked to rank the tasks on a 1 to 10 scale (where 10 is easy) with regard to the ease of navigation and the series of events leading to the result.

The results of this study showed that to accomplish these tasks, HAPPY ASSISTANT required less time and user movements (mouse clicks) than the menu-driven system. Specifically, HAPPY ASSISTANT reduced the average number of clicks by 63 percent and the average interaction time by 33 percent (compared with a menu-driven system). Furthermore, the less experienced users preferred the natural language–enabled navigation much more than the experienced users. Table 1 shows the rating from different user groups in terms of the ease of use of the two systems. Overall, respondents preferred the natural language dialog–based navigation (HAPPY ASSISTANT) to the menu-driven navigation two to one (2:1).

In this study, we also found that users are accustomed to typing in keywords or simple phrases (for example, *moderately priced laptop, computer with internet access + games, a high-speed computer*). Despite the moderator's assurance that the user could type anything he/she wanted, complete sentences were seldom observed. The average length of a user query was 5.31 words (with a standard deviation of 2.62). Analysis of the user queries reveals the brevity and relative linguistic simplicity of the input; hence, shallow parsing techniques seem adequate to extract the necessary meaning from the user input. Therefore, in such context, sophisticated dialog management is more important than the ability to handle complex natural language sentences. We also learned that to improve the functions of an electronic-business site, the natural language dialog nav-

igation and the menu-driven navigation should be combined to meet users' needs. Although the menu-driven approach can provide choices for the user to browse around or learn some additional information, the natural language dialog provides the efficiency, flexibility, and the natural touch to the users' online experience. Moreover, in designing natural language dialog–based navigation, one of the key issues is to show users that the system understands their requests before giving any recommendation or relevant information.

## Prototyping

Based on what we learned from the first user study, we developed the NATURAL LANGUAGE SALES ASSISTANt (NLSA). NLSA applied a shallow noun phrase parser to process user input. To enhance the dialog capability, NLSA used a mixed-initiative, state-based dialog manager. Because the first user study highlighted a definite need for system acknowledgment and feedback, NLSA incorporated an explanation model that explained to the user what was understood and why a particular product was recommended. Furthermore, NLSA addressed the issue of real-time data management and provided tools for managing data and knowledge used in online interaction. A detailed description of NLSA can be found in Chai et al. (2001b).

Prior to the development of NLSA, we conducted a user survey to help understand specific user needs and collect user vocabulary. Users were given three sets of questions. The first set contained three questions: (1) What kind of notebook computer are you looking for? (2) What features are important to you? (3) What do you plan to use this notebook computer for? By applying statistical *n*-gram models and a shallow noun phrase grammar to the user responses, we extracted keywords and phrases expressing users' needs and interests. In the second set of questions, users were asked to rank 10 randomly selected terms from 90 notebook-related terms in order of familiarity to them. The third set of questions asked for demographic information about users such as their gender, years of experience with notebook computers, and native language. We derived correlations between vocabulary-terms and user demographic information. This study allowed us to group technical terms into different complexity groups and better formulate system responses to different user groups. Over a 30-day period, we received 705 survey responses. After approximately 400 responses, the number of extracted keywords and phrases started to converge. From this survey, we extracted 195 keywords and phrases. These keywords and phrases helped us jump-start the development of NLSA. We believe this kind of market survey could be one approach to help customizing our technology to a different domain.

We also conducted the second user study to test the usability of NLSA. In this study, we focused on evaluating the dialog flow and the ease of use. Thirty-four subjects with beginner or intermediate computer skills were interviewed for the study. Again, they were asked to find laptops for a variety of scenarios using three different systems: (1) the NLSA, (2) a directed dialog system (through predesigned questions and answers), and (3) a menu-driven navigation system. Participants were asked to rate each system for each task on a 1 to 10 scale (10 being easiest) with respect to the ease of navigation, clarity of terminology, and their confidence in the system responses. The focus of the second study was to compare systems of similar function and draw conclusions about the functions of NLSA.

The results showed that the users clearly preferred dialog-based searches to non–dialog-based searches (79 percent to 21 percent). Furthermore, they liked the narrowing of the product list based on identified constraints as the interaction proceeded. Our analysis reveals statistical differences in terminology ratings among the three systems for the category of beginner users only. There were no statistical differences found in the other ratings of navigation and confidence across the three sites for different categories of users. The results suggest that asking questions relative to the right level of end-user experience is crucial. Asking users questions about their lifestyle and how they were going to use a computer accounted for a slight preference for the directed dialog system over the NLSA, which uses questions presented on the basis of understanding features and functions of computer terms.

Again, as in the first user study, we learned that it is important to show users that the system understands them. Users remarked in our study that they appreciated the recommended results because the system offered some explanation. This feature allows the user to trust the system. Good navigation aids can be provided by summarizing the user's requests, paraphrasing them using context history, engaging in conversations with the user. Our studies found that robust natural dialog had a big influence on user satisfaction—almost all the respondents appreciated the additional questions prompted by their input and the summary of their previous queries.

The studies pointed toward improvements in the area of system responsiveness, including

tuning up the follow-up questions, prompts, and explanations to the user's input. To a large extent, the success of a dialog system has been shown to depend on the kind of questions asked and the type of feedback provided. User's confidence in the system decreases if the system responses are not consistent with the user's input. The system feedback and the follow-up questions should manage a delicate balance between exposing system limitations to the user and making sure the user understands the degree of flexibility and advantages of using a dialog system.

### Pilot Deployment

We made further improvements to NLSA based on the results of the user studies and deployed NLSA on an external IBM web site for a few months as a pilot. During the pilot, we collected valuable feedback from real users that greatly helped subsequent system improvements.

For the pilot data, the average user query was 6.1 words long, which is significantly higher than the roughly 2.2 words a query for search engines. We also found that users were open to typing in long natural language expressions to find ThinkPads. The maximum query length was over 150 words long.

Perhaps the most surprising finding of the pilot study was that a large proportion of user queries were technical in nature, expressing very specific needs about different product attributes. Users freely (and without any coaching or guidance) expressed relational operators (for example, *less than, at least, etc.*) and conjunctions of multiple constraints. This suggests that NLSA is useful for technology-savvy users, enabling them to quickly get to the products of interest to them. Moreover, if a user has very specific technical requirements (for example, *an xga computer with at least 20 gb, 128 mb ram, and 15" tft display*), NLSA is often the best mechanism for finding the relevant products quickly (compared to keyword search or menu-driven navigation).

### Postpilot Enhancement

Having carried out the two user studies and learned the lessons from the pilot deployment, we are now developing the third version of the system: the NATURAL LANGUAGE ASSISTANT (NLA). The system described in this article is the result of this effort.

In particular, as described earlier, we redesigned the questions that NLA asks users to be simpler and focus on usage patterns rather than technical features. Subsequently, we added functions that classified users into general versus technical categories. If the technical category of users was detected, a technical pool of questions would apply. We also integrated a statistical parser with NLA to more robustly handle varied user input. The statistical parser should enable NLA to scale to multiple languages and multiple domains in a more robust and reliable fashion. In addition, we have designed a more uniform, more compact, and consistent user interface.

While developing NLA, we iterated through various design phases, as described earlier, which helped us learn more about user requirements and system limitations and enabled us to incrementally improve the system in a systematic fashion. Our studies confirmed the hypothesis that a natural language dialog interface is a significant improvement over existing product-retrieval mechanisms. In future studies, we would like to focus more on defining quantitative and objective measures of system's success.

## Conclusion

This article describes a natural language dialog system that helps users find products satisfying their needs on electronic-commerce sites. The system leverages technologies in natural language processing and human-computer interaction to create a faster and more intuitive way of interacting with web sites. By combining techniques in robust statistical parsing with traditional AI rule-based technology, the system is able to accommodate both customer needs and business requirements.

Our studies show that dialog-based navigation is preferred over menu-driven navigation (79 percent to 21 percent) and confirm the efficiency of using natural language dialog in terms of the number of clicks and the amount of time required to obtain the relevant information. Compared to a menu-driven system, the average number of clicks used in the natural language system was reduced by 63.2 percent, and the average time was reduced by 33.3 percent. In a pilot study, we found that when presented with the right interface, users do type long, technical queries (average of 6.10 words a turn), for example, expressing relational constraints on multiple product attributes or usage categories. Moreover, our pilot study revealed that technical users were able to use NLA successfully to quickly find products of interest to them. Thus, a shallow natural language layer on top of a relational database offers a powerful alternative to traditional keyword search or menu-driven systems for electronic-commerce sites. Additionally, the use of a thin dialog layer makes the system accessible

to all types of users and greatly enhances the user experience.

Natural language dialog interfaces offer a more natural mode of interaction than traditional user-interaction mechanisms such as a command-driven interface, a form-filling interface, question-answer sequences, and menus. However, natural language dialog also faces serious challenges. For novice users, a conversational system can be overwhelming, and it can be quicker to use a menu-driven system. For experienced users, the amount of typing can be a drawback, and browsing might be the best and quickest way to navigate. Ultimately, to satisfy different user needs, the natural language dialog navigation and the menu-driven navigation should be combined. Although the menu-driven approach provides choices for the user to browse or learn some additional information, the natural language dialog provides the efficiency, flexibility, and natural touch to the user's online experience.

Furthermore, conversational interfaces offer the ultimate kind of personalization. *Personalization* can be defined as the process of presenting each user of an automated system with an interface uniquely tailored to his/her preference of content and style of interaction. Thus, mixed-initiative conversational interfaces are highly personalized because they allow users to interact with systems using the words they want and fetch the content they want in the style they want. Users can converse with such systems by phrasing their initial queries at the right level of comfort for them (for example, *I am looking for a gift for my wife* or *I am looking for a fast computer with DVD under $1500*).

In the next few years, natural language dialog should become the preferred mode of interaction with institutional knowledge as well. Hence, our effort in building NLA can be viewed as a prelude to other, similar more advanced systems. Although the existence of a product hierarchy and a limited number of product parameters makes electronic commerce a natural domain for natural language dialog systems, our approach can naturally be expanded to industrial and enterprise domains outside electronic commerce for which well-defined ontologies are available. Similarly, we expect that the lessons learned about engineering the interactions to be applicable there. Our work in knowledge update processes done as part of this project might eventually be expanded to address knowledge infrastructure in other domains (we see it as an interesting open problem). These three problems—ontology, HCI, and knowledge architectures—cover the basic pragmatics of engineering interactive knowledge systems.

## Acknowledgments

We would like to thank John Karat and Catherine Wolf for input on user testing and user interface design; Jimmy Lin and Yiming Ye for contributions to the first version of the system and the first user study; Sunil Govindappa for contributions to the second version of the system; Xiaqiang Luo, Niyu Ge, and Salim Roukos for help in transitioning to the new statistical parser; Jose Menes for tools for user session analysis; Tomek Czajka for maintenance tools; and colleagues from the Conversational Systems Group at IBM for illuminating discussions.

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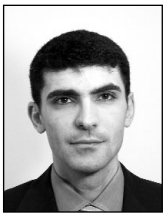

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