# **PRUDENT\*** - A Generic Dialog Agent for Information Retrieval That Can Flexibly Mix Automated Planning and Reinforcement Learning

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#### Abstract

With easy availability of large data sets online, like product catalogs and open data, a common business problem is to allow users to search them for information. However, this information is inaccessible to a lot of people as they are unaware of query languages used for searching through data. In this demonstration, we present PRUDENT - where we harness the power of dialog systems to help the user search for information using natural language. PRUDENT makes use of a planner to adapt to the content structure of the data source and retrieve results, thereby, making the dialog agent generic. However, PDDL based planning needs models and one would want to learn plans over time. Hence, RL based plan generation is also desirable. We show a system which can do this and demonstrate the viability of our approach on large data sets of UNSPSC and ICD-10. The demo video is available at https://youtu.be/X2l7eW6dyBc.

#### Introduction

The widespread availability of data online leads to the importance of gleaning information more than ever. The common methods for information retrieval are by using either specialized languages like Structured Query Language (SQL) or the tedious process of sifting and sieving through the huge corpus of data - which are neither effective nor accessible to diverse users and data sources. We seek to make data accessible to users using the natural interface of dialogs.

Information retrieval using dialog systems is analyzed indepth in (Radlinski and Craswell 2017). The recent trend in research is to train the dialog system from end-to-end, allowing error signal from the end output (system) utterance to be back-propagated to raw (user) input, so that the whole dialog can be jointly optimized. However, major caveats with these systems are that (a) they need large corpus of training data, and (b) once trained and deployed, they do not offer an ability to control the flow of conversation which is desirable in high-stakes domains like health and law. This has lead to renewed interest in inference-based methods to control system behavior(Cohen 2019). In this demonstration, we present PRUDENT - a generic dialog system that is capable



Figure 1: Information lookup on UNSPSC with term - *code for pliers*.

of retrieving information from data sources. The dialog system is built using a reinforcement learning (RL)-based platform, ParlAI (Miller et al. 2018) integrated with automated planning. RL is used to automate the selection of appropriate data source based on the user's query. Once the source is selected, the planner helps in adapting to the content structure of the data source and retrieve results satisfying the user's query.

The system is able to navigate the ambiguity of request, the complexity of content (size, hierarchy, schema) and usage considerations (response time, dialog length) to create a series of conversation leading to the system providing user the appropriate information. One of the highlights of the approach is that the system is general with respect to data sources. The user can start the conversation with no data source and select them one by one, and the system can answer queries across them seamlessly. We give a brief description of the approach here; more details about the system approach, data sources mentioned and preliminary experiments can be found in (Pallagani and Srivastava 2021).

### Demonstration

We demonstrate the generality of PRUDENT using two large datasets: UNSPSC and ICD-10. United Nations Standard Products and Services Code (UNSPSC<sup>1</sup>), is *"is an open, global, multi-sector standard for efficient, accurate classification of products and services"*. It has 4,302 items arranged into class, family, segment and commodity (lowest level). A query on *pliers* may refer to 28 different

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<sup>&</sup>lt;sup>1</sup>https://www.unspsc.org/



Figure 2: Information lookup on ICD-10 with term - *injury* of ulnar artery at wrist and hand level.

kinds of pliers (*Brake Spring pliers, Surgical pliers, etc.*), categorised into 5 classes (*Vehicle Servicing, Orthodontic and Prosthodontic equipment, etc.*), belonging to 4 different families (*Hand Tools, Surgical Products, etc.*). In Figure 1, a snapshot of user conversation in UNSPSC is shown where the user selects the data source explicitly.

Another public data source we use is the International Statistical Classification of Diseases and Related Health Problems (ICD<sup>2</sup>), from the World Health Organization. ICD provides a medical classification to identify diseases, signs and symptoms, abnormal findings, complaints, social circumstances, and external causes of injury or diseases. Medical practitioners extensively refer to ICD to obtain the codes for queries such as *injury of ulnar artery at wrist and hand level*. We use ICD-10-CM which contains 94,766 codes, divided into 22 chapters. Figure 2 shows sample conversations using automatic source selection.

## System Framework

Figure 3 shows the high-level system architecture of PRU-DENT. It consists of three major components - ParlAI core, Planner<sup>3</sup> and an Executor. ParlAI provides the interface for

<sup>2</sup>https://www.cdc.gov/nchs/icd/index.htm

<sup>3</sup>http://solver.planning.domains is used in PRUDENT



Figure 3: System Architecture of PRUDENT

the dialog agent to interact with the user. The Planner, along with ParlAI core helps in *Intent Identification*. The learnt policy (present in ParlAI core) helps in the data *Source Selection* that matches the user's query. The Planner then generates a plan for the Executor, to perform *Information Retrieval* from the selected data source.

**Intent Identification:** Identifying intent is the most crucial step in a dialog setting. However, establishing what the user wants in a single iteration of dialog is an ideal case, and often requires multi-turn dialog exchanges. The planner helps PRUDENT choose the right question to pose to the user in order to glean the most information that would help identify intent in the least number of steps. In addition, PRUDENT also offers the flexibility to use RL for response generation, which is the default operation of ParlAI. Once the intent is identified, the control is transferred to the source selector which is responsible for selecting the appropriate data source.

**Source Selection:** Typically, a user manually selects the data he wishes to query. In addition to manual selection, our approach also offers the flexibility for automatically selecting the data source. ParlAI learns the policy to identify the data source based on the user's intent. For instance, if the recognised user intent is *code for pliers*, with no explicit mention to the data source, the system's learnt policy identifies *UNSPSC* to be the source to look for information.

**Information Retrieval:** Once the data source is identified matching the query, the user can proceed with retrieving information. The user's queries are generally abstract in nature and would need further disambiguation in most of the cases. Often, there is no exact match that satisfies the user's intent and the planner discovers the navigation patterns in the data source, and generates a plan for disambiguation of the user's query. The disambiguation approach followed is to proceed from the highest hierarchy. The planner generates a plan to guide the executor in helping the user reach the goal optimally (in a search sense).

Prudent is currently a proof-of-concept and initial experiments show it to be promising. In future, we plan to explore different integration strategies for planning and RL, conduct experiments and expand to more data sources.

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