Intent-Context Fusioning in Healthcare Dialogue-based Systems using JDL Model

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Abstract A revolutionized wave of intelligent assistants has emerged in daily life of human over the recent years, therefore huge progress has been witnessed for development of healthcare assistants having the capability to communicate with users. However, the conversational complexities demand building more personalized and user-oriented dialogue process systems. To support human-computer dialogue process many models have been proposed. Considering personalization aspect, this research work presents novel Context-aware Dialogue Manager (CADM) model with its foundation based on well-known JDL fusion model. The proposed model addresses modern techniques for multi-turn dialogue process, by identifying dialogue intents, contexts and fusing personalized contexts over them. The model also maintains the dialogue context for progressing complex and multi-turn dialogue. It also helps using intent-context relationship in identifying optimized knowledge source for accurate dialogue expansion and its coherence. CADM functionality is discussed using support of Intelligent Medical Assistant in healthcare domain, which has the speech-based capability to communicate with users.

Keywords: Intent Recognition, Context Identification, Intent-context fusioning, Ontology

1 Introduction

In this era of digital world, dialogue based systems have been introduced in human daily life in several forms. They can be conversational systems, virtual assistants, robots or chat-bots. They are useful in a wide range of applications ranging from daily life entertainment to healthcare. Most important is that, they have the capabilities of conversational interaction with underlying speech and language understanding. In healthcare domain, intelligent medical assistants have also been introduced for personalized-care and assistance services. Intelligent medical assistants provide interactive and seamless dialogue process to its users for health related queries. However, there is still a need for devising an efficient mechanism for identifying dialogue intents and management of context for multi-turn dialogue process. In order to proceed with dialogue strategy, another important task is to choose proper system of actions, with underpinning reference of appropriate knowledge-base for effective question answering. To strengthen the decision of responsive system actions, recognition and maintenance of dialogue context from on-going multi-turn dialogue can provide effective mechanism for selecting suitable knowledge-base for efficient dialogue response.

2 Motivation

Most of the proposed Dialogue manager lack insights regarding conversational dialogue contexts. In this study besides, identification of dialogue intents, we also focused on observing their relations with dialogue contexts so that effective dialogue management process can be performed. Based on current state of the art, we figured out some of the key limitations, challenges and proposed our solutions as mentioned in Table 1. The main contributions of this paper depends on identified limitations.

Current Focus	**Limitations & Challenges**	**Solutions**
Intent Recognition[5]	Lack Semantic relationships for accurate Intent Identification	• Context-aware Dialogue Ontology development. • Ontological Modeling for Intent identification.
Context Management	Little or no attention given to maintain and coalesce dialogue contexts, their switching & expansion.	• Semantic Mappings amongst Intent and Contexts. • Design SPARQL queries to interact with Ontological Model for text/speech based dialogue process.
Intent-Context Fusioning[8]	Lack of personalization effect	Besides Dialogue context additionally inclusion of personalization contexts like location, environmental etc.
Appropriate Knowledge Sources Referral	Crawls web, searches all repositories by Dialogue manager for efficient answers	Model Prioritized knowledge sources Information.
Response Generation	Lack context-aware personalized response	Fusioning of personalized contexts with response

Table 1: Limitations, Challenges and Solutions

The rest of the paper is organized as follows. Section 3 describes survey work that is related to the topic of this paper. Section 4 describes the component level insights of architecture for Context-aware dialogue manager which we proposed. Section 5 implementation of CADM in healthcare domain. Finally, main conclusions and future road map are presented in Section 6.

3 Related Work

In last decade dialogue based management systems such as virtual assistant, chat-bots, healthcare assistants have gained popularity with dialogue management aiming to provide good interaction. Intents identified during conversational dialogue are closely related to context, which includes not only external environmental contexts like time, location, temperature but also personal daily life contexts. The relationship between context and intent is complicated, which exhibits complex co-occurring and sequential correlation [11]. Context itself also consists of numerous heterogeneous entities collected from various sources, and these entities mostly are of diverse in nature. Therefore, it is challenging to model the context-intent relationship. Moreover, to track users' intent-context relationship in real-time is even more challenging as personal assistants have to pay attention to the personalized contexts. An overview of intent recognition approaches [7], relationship among different states belonging to different objects in an area of interest for given point in time have been sketched. In this study authors suggested that inclusion of additional dialogue states have impact on recognizing more sub-intentions, which leads to the proper task completion for intention recognition in dialogue process. The Dialogue State Tracking Challenge (DSTC) also provides a forum in dialogue state tracking in spoken dialogue systems. For instance, DSTC-5 mainly refers to track dialogue states based on sub-dialogue segments for TourSG dataset [4]. In this challenge, most researchers based on hypothesis contributed several results for the each turn for a given sub-dialogue by considering dialogue context history. Researchers are more focused with how to make robots for more engaging to people [1] using different methods to exploit use of sensors for identifying the physical contexts. This work aims at contextualizing the additional information conveyed during the interaction with a robot, by using information enrichment techniques. In this study, researchers rely on semantic techniques to extract from users' inputs information related to their moods, to the main entities and concepts they were mentioning, to the topic they are talking about and to other information such as time or money expressions. In the work by [3] have highlighted the importance of *understanding intentions* in context is an essential human activity during conversation. Similar likelihood will be considered as important as for any robot if its functionality is required in any social domains. The development of context-based fusion system mainly relies on the quality of fused inputs and their usage for domain-adapted solutions [9]. In this fused input role of context is non-trivial in modern fusion systems which is specifically addressed in Joint Directors of Laboratories- Model (JDL). The JDL model, in order to gain adaptability and improved performance supports object recognition by exploiting physical context, and estimate intents using linguistic conversational analysis.

3.1 Information Fusion Model

Our investigation for finding state of the art in the field of information fusion have considered work presented by [6] in which they highlighted different data/information fusioning techniques required for intent recognition and context determination. The findings are reported in Table. 2.

Category	Model	Features
Information-Based Models	• Joint Directors of Laboratories (JDL) • Data Feature Decision (DFD)	Based on the abstraction of the data generated during fusion process
Activity-Based Models	• Boyd Control Loop • Intelligence Cycle • Omnibus model	Based on activities that must be performed by Fusion System, Activities and Correct sequence of execution are explicitly specified
Role-Based Models	• Object Oriented Model • Frankel-Bedworth Architecture	Based on Fusion roles and their relationships

Table 2: Information Fusion Models and their features

3.2 JDL Model

The US Joint Directors of Laboratories (JDL) Data Fusion Sub-Group initially proposed JDL Model for data fusion and introduced its functions in 1985 which was later updated in 1998 [10]. In the study [9] Snidaro et al., provided comprehensive status of context-based information fusion systems and explored novel context exploitation dynamics and architectural aspects such as incorporation of Contextual Information in JDL Model. The study demonstrated and differentiated *functions* into *fusion levels* by providing important distinction among information fusion processes. The derived JDL Model relates refinements for parameters of interest at 5 levels. Data source are responsible for providing input

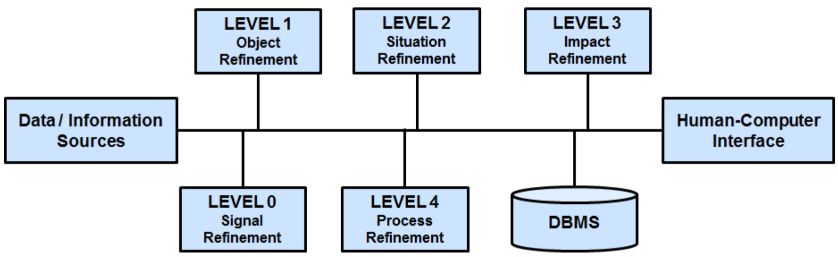

Figure 1: JDL Data Fusion Model derived from 1999 revision[10]

to the JDL model, it can be of any form, like sensory, human interaction or any other system [6]. DBMS provides data management support required to process within in JDL data fusioning whereas human-computer interface provides interface to interact with system in obtaining the desired fused results as shown in Fig. 1. The details for layers are as under.

- *Level 0 (Signal Refinement):* This level is for estimation, association, characterization and prediction for signals. Several preprocessing tasks related to data, such as normalization, missing values, incomplete data sets, and filtration of low quality measurements are performed in this level.
- *Level 1 (Object Refinement):* This level on the basis of inferences from observation performs estimation and prediction for entity states. This level performs key role for transforming data into consistent structure with objects identification based on inference.
- *Level 2 (Situation Refinement):* To identify a situation a contextual description of the relationship among entities and observations by using a-priori knowledge and environmental information is obtained in this level.
- *Level 3 (Impact Refinement):* To deal with the impact of effects on situations or predicted actions i.e. evaluate the current situation and predict possible threats.
- *Level 4 (Process Refinement):* This is responsible for data acquisition and source allocation to support mission objectives. It also monitors the system performance according to the specified goals.

4 CADM: Context Aware Dialogue Manager

The proposed model Context-aware dialogue manager (CADM) is based on JDL fusion model. Special attention has been considered while designing CADM and associated its work-flow corresponding to the layers of JDL Model.

4.1 CADM: Component Level Details

This proposed model disclosed herein, comprises of a subcomponents for modeling the user dialogue with system. This study covers the domain of dialogue-based systems, where system communicate with user through speech. This system can be Intelligent Medical Assistant (IMA) or health assisted robot facilitating users to interact using conversation for healthcare issues, diagnosis, appointments etc. The subsequent sections describe the component level details.

Sub-dialogue Builder: The sub-dialogue builder is responsible for conversion of entities obtained from speech language understanding into ontological form as per Context-aware Ontology (CADO). This component holds capability to complete sub-dialogue as there can be some noise and some keyword might be missing from SLU.

- *Utterance Mapper:* The Utterance Mapper a component, which is responsible for generating ontological models for sub-dialogue entities. These entities are

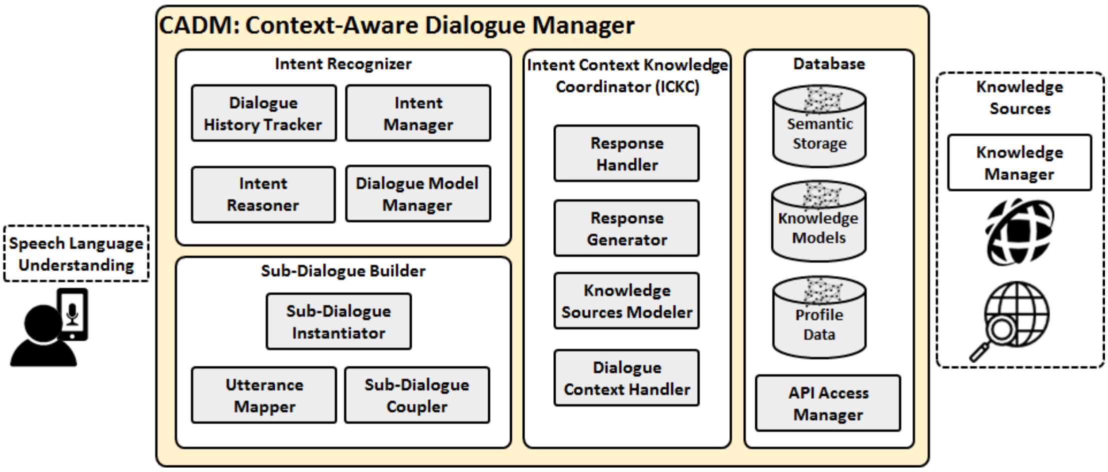

Figure 2: Context Aware Dialog Manager Architecture

obtained from speech language understanding. Utterance mapper transforms these entities into corresponding ontological model concepts called utterance triples. It also converts meta-data like user information and time into ontological form. These utterance triples are stored in semantic storage using Dialogue Context Handler which coordinates with database storages.

– *Sub-Dialogue Coupler:* The Sub-Dialogue Coupler is responsible to receive the utterance triples and arrange relevant utterance triples obtained from utterance mapper, which might have been received with delay or missing due to some noise or misunderstanding from speech language understanding. This component retrieves the concurrent utterance triples from semantic storage through dialogue context handler.
– *Sub-Dialogue Instantiator:* The sub-dialogue instantiator creates new ontological instance called *apparent sub-dialogue instance*, linking similar and non-similar utterance triples obtained from sub-dialogue coupler. Once the apparent sub-dialogue instance is created, it is given to dialogue model manager.

Intent Recognizer: The Intent Recognizer component provides diverse functionalities by verifying the apparent sub-dialogue instance, identifying context history, and inferring intents before routing the desired information to the knowledge sources. Its working is dependent on coordination of Dialogue Model Manager, Dialogue History Tracker, Intent Reasoner and Intent router.

– *Dialogue Model Manager:* The apparent unclassified sub-dialogue model is received Dialogue Model Manager. This component verifies the apparent unclassified sub-dialogue model semantically and syntactically verses CADO through Dialogue context handler. Once the apparent unclassified sub-dialogue context is validated, this instance is provided to intent reasoner.

– *Intent Reasoner:* The Intent Reasoner identifies the Intent of apparent unclassified sub-dialogue instance. This classification of the apparent unclassified sub-dialogue based instance into conversational intent is based on inference functionalities provided by the CADO. Using the ontological reasoner such as Pellet[1], an automatic classification is performed over apparent unclassified sub-dialogue instance. This apparent unclassified sub-dialogue instance is compared by the definitions of different intents to determine whether these conditions complies with the intent definition or not. In affirmative case, the apparent unclassified sub-dialogue is considered to be inferred to be part of intent. This intent reasoning process gets triggered whenever dialogue model manager sends verified apparent unclassified sub-dialogue instance to intent recognizer. Otherwise, if the intent membership could be classified than this apparent unclassified sub-dialogue instance is delivered further without intent identification to find out the response from the knowledge sources. In both the cases intent information along-with sub-dialogue information is passed to the dialogue history tracker.
– *Dialogue History Tracker:* Dialogue consists of several sub-dialogues, with each sub-dialogue can have different or same intents. Monitoring and keeping dialogue consistent with context, dialogue history tracker performs key role based on current apparent unclassified sub-dialogue model. This previously contextual state is retrieved using SPARQL queries from semantic storage. This component activates the model enrichment process, by identifying if there exist certain intent/context for apparent unclassified sub-dialogue model. This component retrieves contextual information from profile data. This component helps in use for adaptation like user interest, previous contexts obtained from profile data. It basically refines the criteria by fusing additional information to the intents, like profile information, which helps for creating appropriate response generation.
– *Intent Manager:* After the intent has been identified, the sub-dialogue and intent is provided to intent manager. Intent manager before notifying has two more tasks to perform, i.e. fusing the personal context and identifying the knowledge source for further dialogue action. Intent manager requests knowledge source modeler. This component has the capability to respond, based on sub-dialogue model and intent using SPARQL. The determined intent plays vital role in identifying the appropriate knowledge source. This knowledge source information is modeled in the repository Knowledge models. The obtained knowledge source information, intent along with sub-dialogue information is referred to knowledge source for reply. Our system works for healthcare domain, in which entities are gathered from user using speech based devices. This information based on entities, intents and appropriate knowledge source is forwarded to Knowledge Manager, a component for coordinating Knowledge sources which helps in expanding dialogue using further questioning or response generation by knowledge sources.

[1] https://www.w3.org/2001/sw/wiki/Pellet

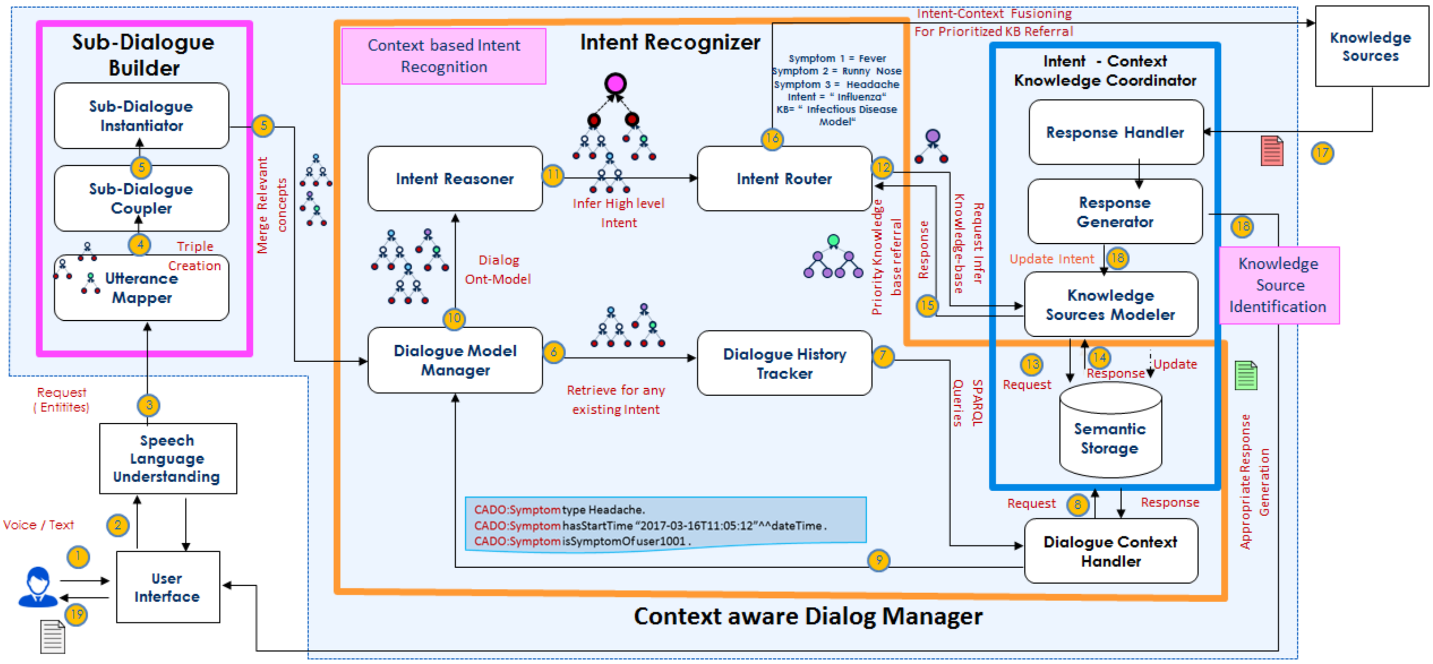

Figure 3: Context Aware Dialog Manager detailed Work-flow

Intent-Context Knowledge Coordinator: This component Intent-Context Knowledge Coordinator provides full functionalities support to CADM. This component supports coordination between sub-dialogue builder, Intent Recognizer and Database Storage. It coordinates for storing newly mapped utterances, retrieval and loading of CADO, and also persistence of updation to the knowledge source mappings with intents. Besides all, It also facilitates for generation of responses and helps in dialogue progress. The sub components include terminology definitions, communication mechanism using SPARQL query language among components and Database Storage infrastructure.

– *Dialogue Context Handler:* The Dialogue Context Handler provides interaction and management facilities with Context-aware dialogue ontology (CADO) model stored in semantic storage. This component is responsible for providing three types of supports to CADM. It provides management facilities for inter-component interaction. It performs CADO loading into memory so that the concerned components can readily use it. It also holds automatic extension to the CADO once some extension is required in terms of CADO terminology, Intent-concept mapping etc. The extended CADO is evolved in terms of new definitions and rules determining new or updation of existing intents. The Dialogue Context Handler ensures ease of use for the latest CADO by respective components of systems as discussed in different sections.

- *Knowledge Source Modeler:* The component Knowledge Source Modeler play two major roles. One of them is identifying and optimizing prioritized knowledge source model amongst various knowledge models stored in Knowledge Model Database storage. The Intent Manager, for identifying prioritized knowledge source referral based on identified conversational intent, generates this request. The second key role is to persist the knowledge source model information and its relationship with intents so that it can be made available for conversational intents for the management of dialogue process.
- *Response Handler:* The component Response Handler gets triggered, when Knowledge Manager gathers information based on the input generated by the Intent Manager or if unnecessary delays incurs. This component takes care of two important aspects, one of which is handling the response based on information gathered from the knowledge manager and other is to engage user if relevant response generation gets delayed.
- *Response Generator:* Based on the responses delivered by Response Handler, this component initiates dialogue response which is forwarded to text to speech component.

Storage: Several storage strategies were considered in CADM discussed briefly as under.

- *Semantic Storage:* The Semantic Storage is a database storage, which provides persistence to the CADO. This includes both the CADO definition terminologies and rules. Since sub-dialogue are modeled using CADO and intent is inferred over them. The semantic storage follows triple storage framework mechanism, in which all sub-dialogue concepts, intents are converted into triples. The read/write interactions among sub-dialogue triples are supported by dialogue context handler component in the ICKC layer.
- *Knowledge Models:* The Knowledge Models storage provides facility to knowledge model information and their relationships with conversational intents. This involves intervention from Ontology Engineer Expert for verification because of the criticality of health domain. These knowledge models are not in detail but holds meta-data information with intent relationships only. The detailed information resides with Knowledge Sources. Whenever new Knowledge source is added, or intents definition needs to be related to the knowledge source, this information is passed by Knowledge Manager to the Knowledge sources Modeler via Response Handler which updates.
- *Profile Data:* The necessary information pertaining to user lies with Profile Data storage. As this study targets health related conversation management, so this repository will have information like past medical history, allergies, nutrition choices etc. This personal information enriches the intent and is fused while retrieved through dialogue history tracker.
- *API Access Manager:* This component is activated when user's contexts like location, environmental information such as weather, temperature needs to be determined. Just like personal information additionally the on demand

contextual and environmental information collected via API Access Manager which provides access to external applications in the Knowledge Sources.

4.2 CADM and JDL Model

The survey conducted by Snidaro et al. [9] provides several existing definitions of context in literature with highlighting the most important evidences for inclusion of Contextual Information in different domains. It provides a comprehensive overview how contextual information fusion can play important role in the domains like mobile and pervasive computing, healthcare, image processing, artificial intelligence knowledge-based systems etc. They provided insights to various techniques applied to all levels of JDL model and categorized levels into Low-Level Fusion and High-Level Fusion. Low-level included Level 0 and Level 1 whereas high-level included Level 2, Level 3 and Level 4. They provided detail description over the importance of contextual information in high-level fusion processes (Level 2-4). They separated knowledge representation, intent assessment, decision making and process refinement functions by introducing extensive context discover, adaptation and learning techniques. For knowledge representation and establishing the relationship among multi-domains they highlighted the role of ontologies for context representation. Level 3-4 fusion is mostly concerned with high-level contextual knowledge extraction from low level fusion processing [2] in particular Level 3 for intent prediction and Level 4 for process control, mission management and source requirement determination in knowledge based systems.

5 Case Study: Intelligent Medical Assistant (IMA)

In conversational and dialogue based systems most of the examples are tailored to the characteristic of particular problem related to specific domain. However less importance was given to design a dialogue manager which fulfills all requirements for Information Fusion prescribed by JDL Model. In this study, we proposed a generalized CADM which works based on JDL Model. The components are designed in a sense that they comply with the JDL functionalities distinguishing all entities separately like Intent, context and knowledge information. We demonstrate use of speech based utility in healthcare domain, in which patients are provided voice enabled functionalities like interacting with Intelligent agent. We consider Intelligent Medical Assistant (IMA). IMA has capability to respond user and interact based on questions and queries. The information obtained in the form of text/speech is semantically annotated based on CADO, Intent of dialogue are determined, and context is maintained through out the process as discussed in detail in previous sections. Taking in accounts user's present context, like health conditions, past medical history, location, weather information, past conversational context, transportation, communication type, real-time response generation is considered by CADM. Using the services of CADM in IMA, monitors the dialogue context and user context for appropriate response generations

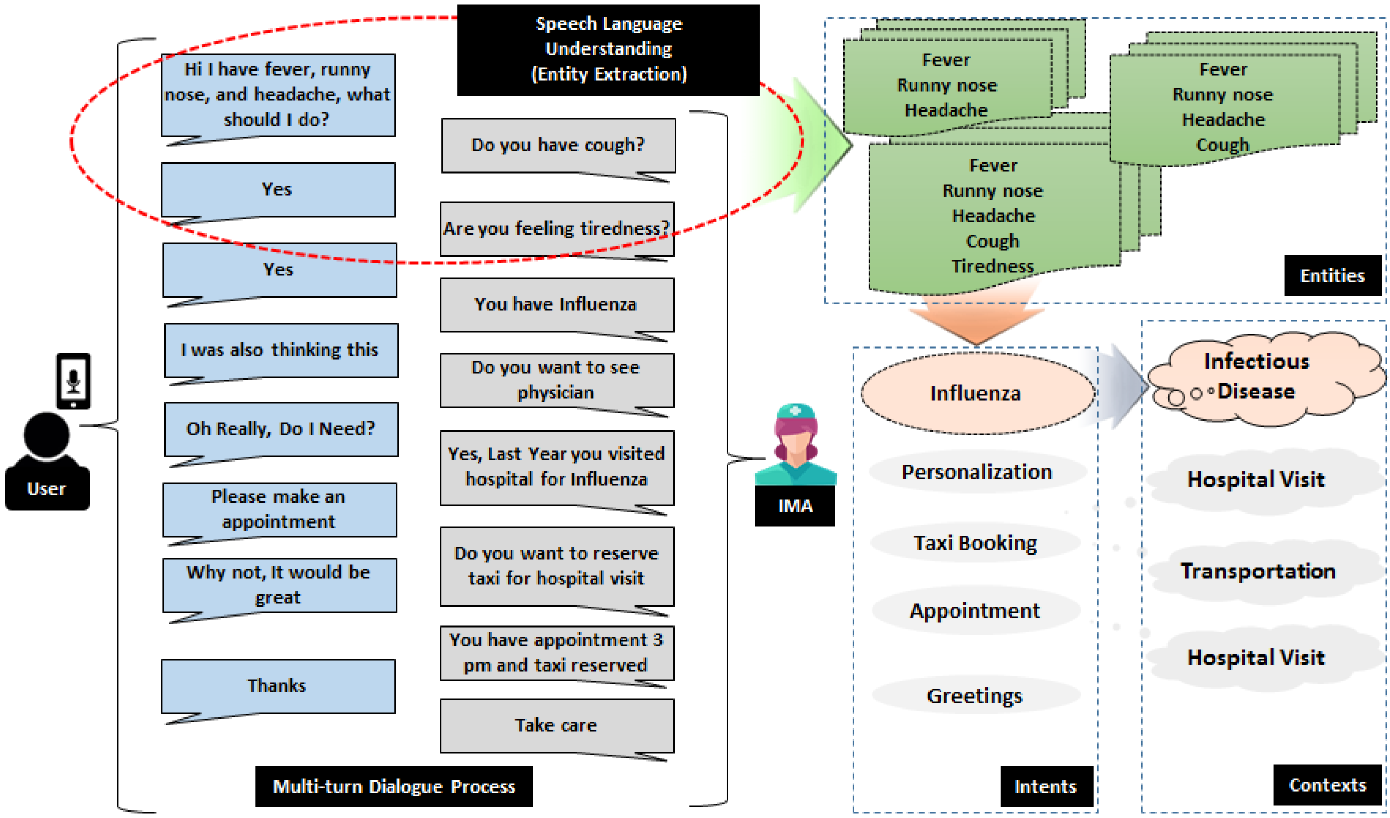

Figure 4: Intent-Context Recognition based on Entities in IMA

from knowledge sources as mentioned in Fig. 4. The CADM is carefully designed and as a test case tailored especially for IMA to keep the reliability, consistency, and relevancy of dialogue of user with IMA. By highlighting the key aspect that intent-context fusioning can play vital role in modern dialogue based systems by intent estimation through linguistic conversation analysis and context determined over it.

6 Conclusions and Future Work

In this paper context-aware dialogue manager (CADM) model is proposed in compliance with JDL for enrichment and completeness for effective conversational service. The presented case study CADM in *Intelligent Medical Assistant* (IMA) indicated the feasibility and usability of proposed model for conversation with user end-to-end. We demonstrated the interaction of different components and their inputs/outputs. We also highlighted the importance of determining intents, identify context and fusing them each other for appropriate responses from knowledge sources. As a future work, we aim to develop CADM with underlying context-aware dialogue ontology (CADO). We plan to evaluate CADM for different domains and measure its correctness, real-time responses and dialogue confidence.

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