

# GENERALISATION OF END-TO-END TASK-ORIENTED DIALOG SYSTEMS TO UNSEEN KNOWLEDGE

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# GENERALISATION OF END-TO-END TASK-ORIENTED DIALOG SYSTEMS TO UNSEEN KNOWLEDGE

by

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# Certificate

This is to certify that the thesis titled **Generalisation of End-to-End Task-Oriented Dialog Systems to Unseen Knowledge** being submitted by **Mr Dinesh Raghu** for the award of **Doctor of Philosophy** in the Department of Computer Science and Engineering is a record of bonafide work carried out by him under my guidance and supervision at the **Department of Computer Science and Engineering, Indian Institute of Technology Delhi**. The work presented in this thesis has not been submitted elsewhere, either in part or full, for the award of any other degree or diploma unless otherwise stated explicitly. In particular, some parts of work in Chapter 3 was done jointly with undergraduate and master's students, some parts of Chapter 4 was done jointly with a master's student, and some parts of work in Chapter 5 was done jointly with an undergraduate student and a research developer. In each case, the part done by the collaborators appeared in their respective theses.

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# Abstract

Task-oriented dialog (TOD) systems converse with users to help them with specific tasks such as calendar enquiry, restaurant reservation, and tourist package recommendation. To achieve task success, TOD systems must interact with a task-specific knowledge source. For example, a restaurant reservation system has to be grounded on a knowledge base that contains the names of restaurants, and their details. End-to-end TOD systems are a type of TOD system that are trained using past human-to-human dialogs and do not require any handcrafted state representations and their corresponding annotations on each dialog.

There are several challenges that prevent end-to-end TOD systems from being used for real-world applications. In this thesis, we address three such challenges. The common theme across the contributions is that the proposed TOD systems that are aimed at tackling these challenges generalize well to knowledge unseen during train. (1) To improve the performance of end-to-end TOD systems grounded on structured knowledge bases, we propose three novel neural models – BoSsNet, MLM-Net and CDNet, (2) to reduce the training cost, we define and study the novel problems of training end-to-end TOD systems without the need for explicit KB query annotations, and (3) to extend the types of knowledge sources supported by end-to-end TOD systems, we define and study the novel task of end-to-end learning of a TOD system that troubleshoots user’s problems by using a flowchart and a corpus of FAQs.



## सार

टास्क-ओरिएंटेड डायलॉग (टी.ओ.डी.) सिस्टम्स उपयोगकर्ताओं की कैलेंडर पूछताछ, रेस्तरां आरक्षण, और पर्यटक पैकेज सुझाव जैसे विशेष कार्यों में मदद करते हैं। कार्य सफलता प्राप्त करने के लिए, टी.ओ.डी. सिस्टम्स को कार्य-विशिष्ट ज्ञान स्रोत के साथ बातचीत करनी चाहिए। उदाहरण के लिए, एक रेस्तरां आरक्षण सिस्टम को एक ज्ञान आधार पर आधारित होना चाहिए जिसमें रेस्तरां के नाम और उनके विवरण शामिल हों। एंड-टू-एंड टी.ओ.डी. सिस्टम्स एक प्रकार के टी.ओ.डी. सिस्टम होते हैं जो पिछले मानव-से-मानव डायलॉग्स का उपयोग करके प्रशिक्षित किए जाते हैं। इन्हें प्रत्येक डायलॉग पर हैंडक्राफ्टेड स्टेट रिप्रेजेंटेशंस और उनसे संबंधित एनोटेशन्स की आवश्यकता नहीं होती है।

एंड-टू-एंड टी.ओ.डी. सिस्टम्स को वास्तविक दुनिया के अनुप्रयोगों में उपयोग करने में कई चुनौतियाँ हैं। इस शोध अध्ययन में, हमने ऐसी तीन चुनौतियों का समाधान किया है। सभी योगदानों में एक सामान्य विषय यह है कि प्रस्तावित टी.ओ.डी. सिस्टम्स, जो इन चुनौतियों को संबोधित करने के लिए बनाए गए हैं, प्रशिक्षण के दौरान अनदेखे ज्ञान के लिए भी अच्छी तरह से सामान्यीकृत होते हैं। (1) संरचित ज्ञान (स्ट्रक्चर्ड नॉलेज) आधारों पर आधारित एंड-टू-एंड टी.ओ.डी. सिस्टम्स के प्रदर्शन में सुधार के लिए, हम तीन नवीन न्यूरल मॉडल्स प्रस्तावित करते हैं -- बॉसनेट, एमएलएम-नेट और सीडीनेट। (2) प्रशिक्षण लागत को कम करने के लिए, हमने एक्सप्लिसिट के.बी. एनोटेशन्स का उपयोग किए बिना एंड-टू-एंड टी.ओ.डी. सिस्टम्स को प्रशिक्षित करने की नई समस्याओं को परिभाषित किया और उनका अध्ययन किया है। (3) एंड-टू-एंड टी.ओ.डी. सिस्टम्स द्वारा समर्थित ज्ञान स्रोतों के प्रकारों का विस्तार करने के लिए, हमने एक नया कार्य परिभाषित किया और उसका अध्ययन किया है। इसमें हम फ्लोचार्ट और एफ.ए.क्यू. की एक संग्रह का उपयोग करके टी.ओ.डी. सिस्टम का एंड-टू-एंड प्रशिक्षण करते हैं।



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