Automatic Intent-Slot Induction for Dialogue Systems

Zengfeng Zeng zengzengfeng277@pingan.com.cn Ping An Life Insurance of China, Ltd.

Dan Ma* whmadan1990@gmail.com Ping An Life Insurance of China, Ltd. China

Haigin Yang hqyang@ieee.org Ping An Life Insurance of China, Ltd.

Zhen Gou

gouzhen508@pingan.com.cn Ping An Life Insurance of China, Ltd. China

KEYWORDS

Intent-Slot Induction, Spoken Language Understanding

ACM Reference Format:

Jianping Shen

shenjianping324@pingan.com.cn

Ping An Life Insurance of China, Ltd.

China

Zengfeng Zeng, Dan Ma, Haiqin Yang, Zhen Gou, and Jianping Shen. 2021. Automatic Intent-Slot Induction for Dialogue Systems. In Proceedings of the Web Conference 2021 (WWW '21), April 19-23, 2021, Ljubljana, Slovenia. ACM, New York, NY, USA, 12 pages. https://doi.org/10.1145/3442381.3450026

INTRODUCTION

Recently, thanks to the advance of artificial intelligence technologies and abundant real-world conversational data, virtual personal assistants (VPAs), such as Apple's Siri, Microsoft's Cortana and Amazon's Alexa, have been developed to help people's daily life [4]. Many VPAs have incorporated task-oriented dialogue systems to emulate human interaction to perform particular tasks, e.g., customer services and technical supports [2].

Spoken language understanding (SLU) is a crucial component to the success of task-oriented dialogue systems [9, 39]. Typically, a commercial SLU system detects the intents of users' utterances mainly in three steps [7, 8, 11, 18]: (1) identifying the dialogue domain, i.e., the area related to users' requests; (2) predicting users' intent; and (3) tagging each word in the utterance to the intent's slots. To appropriately solve this task, traditional SLU systems need to learn a model from a large predefined DOMAIN-INTENT-SLOT schema annotated by domain experts and professional annotators. For example, as illustrated in Fig. 1, given a user's utterance, "What happens if I make a late payment on mortgage?", we need to label the domain to "banking", the intent to "Late due loan", and the slot "Loan" to "mortgage".

The annotation procedure usually requires many domain experts to conduct the following two steps [5, 44]: (1) selecting related utterances from specific domains based on their domain knowledge; (2) examining each utterance and enumerating all intents and slots in it. This procedure, however, faces several critical challenges. First, it is redundant as experts cannot effectively share the common information among different domains. For example, given two utterances "Can I check my insurance policy?" and "Can I read my bank statement?" from the domains of banking and insurance, their intents can be abstracted into "check document". They are usually annotated by at least two experts from different domains, which hinders the information sharing. Second, the labeling procedure may be biased to experts' knowledge and limited by their domain experience. To meet more users' needs, dialogue systems usually

ABSTRACT

Automatically and accurately identifying user intents and filling the associated slots from their spoken language are critical to the success of dialogue systems. Traditional methods require manually defining the DOMAIN-INTENT-SLOT schema and asking many domain experts to annotate the corresponding utterances, upon which neural models are trained. This procedure brings the challenges of information sharing hindering, out-of-schema, or data sparsity in open domain dialogue systems. To tackle these challenges, we explore a new task of automatic intent-slot induction and propose a novel domain-independent tool. That is, we design a coarse-to-fine three-step procedure including Role-labeling, Concept-mining, And Pattern-mining (RCAP): (1) role-labeling: extracting key phrases from users' utterances and classifying them into a quadruple of coarsely-defined intent-roles via sequence labeling; (2) conceptmining: clustering the extracted intent-role mentions and naming them into abstract fine-grained concepts; (3) pattern-mining: applying the Apriori algorithm to mine intent-role patterns and automatically inferring the intent-slot using these coarse-grained intent-role labels and fine-grained concepts. Empirical evaluations on both real-world in-domain and out-of-domain datasets show that: (1) our RCAP can generate satisfactory SLU schema and outperforms the state-of-the-art supervised learning method; (2) our RCAP can be directly applied to out-of-domain datasets and gain at least 76% improvement of F1-score on intent detection and 41% improvement of F1-score on slot filling; (3) our RCAP exhibits its power in generic intent-slot extractions with less manual effort, which opens pathways for schema induction on new domains and unseen intent-slot discovery for generalizable dialogue systems.

CCS CONCEPTS

• Computing methodologies → Discourse, dialogue and pragmatics; • Information systems \rightarrow Query intent.

^{*}Corresponding author.

This paper is published under the Creative Commons Attribution 4.0 International (CC-BY 4.0) license. Authors reserve their rights to disseminate the work on their personal and corporate Web sites with the appropriate attribution.

WWW '21, April 19-23, 2021, Ljubljana, Slovenia

^{© 2021} IW3C2 (International World Wide Web Conference Committee), published under Creative Commons CC-BY 4.0 License.

ACM ISBN 978-1-4503-8312-7/21/04.

https://doi.org/10.1145/3442381.3450026

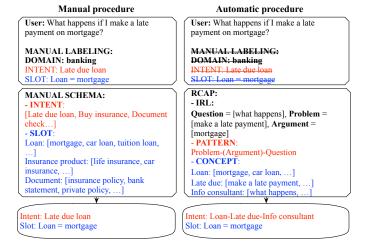


Figure 1: Comparison between traditional manual intentslot construction and automatic induction. The traditional procedure requires domain experts to manually annotate utterances into the DOMAIN-INTENT-SLOT schema (see the left-top box) and many manually annotated schemas (see the left-middle box) while our RCAP can automatically infer the intent-slot without manual labeling.

have to cover a number of domains and solicit sufficient domain experts to build comprehensive schemas. The requirement of domain experts increases the barrier of scaling up the dialogue systems. Third, it is extremely hard to enumerate all intents and slots in the manual procedure. Usually, the intent-slot schema follows the long-tail distribution. That is, some intents and slots rarely appear in the utterances. Experts tend to ignore part of them due to the human nature of memory burden. Fourth, for system maintenance, it is nontrivial to determine whether there are new intents or not in a given utterance. Hence, experts have to meticulously examine each utterance to determine whether new intents and slots exist.

To tackle these challenges, researchers have incorporated different mechanisms, such as crowd sourcing [45] and semi-supervised learning [38], to assist the manual schema induction procedure. They still suffer from huge human effort. Other work further applies unsupervised learning techniques to relieve the manual effort [6, 25, 36, 43]. For example, unsupervised semantic slot induction and filling [6, 25] have been proposed accordingly. However, they cannot derive intents simultaneously. Open intent extraction has been explored [43] by restricting the extracted intents to the form of *predicate-object*. It does not extract slots simultaneously. Moreover, a dynamic hierarchical clustering method [36] has been employed for inducing both intent and slot, but can only work in one domain.

In this paper, we define and investigate a new task of automatic intent-slot induction (AISI). We then propose a coarse-to-fine three-step procedure, which consists of Role-labeling, Conceptmining, And Pattern-mining (RCAP). The first step of role-labeling comes from the observation of typical task-oriented dialogue systems [10, 20, 23, 37, 46] that utterances can be decomposed into a quadruple of coarsely-defined intent-roles: Action, Argument,

Problem, and Question, which are independent to concrete domains. Thus, we build an intent-role labeling (IRL) model to automatically extract corresponding intent-roles from each utterance. By such setting, as shown in Fig. 2, we can determine the utterance of "Check my insurance policy" to Action = [Check] and Argument = [insurance policy] while the utterance of "I lost my ID card" to Problem = [lost] and Argument = [ID card]. Secondly, to unify utterances within the same intent into the same label, as shown in Fig. 5. We deliver concept mining by grouping the mentions within the same intent-role and assigning each group to a fine-grained concept. For example, the mentions of "insurance policy", "medical certificate", and "ID card" in Argument can be automatically grouped into the concept of "Document" while the mentions of "tuition loan" and "mortgage" can be grouped into the concept of "Loan". Here, we only consider one-intent in one utterance, which is a typical setting of intent detection in dialogue systems [24]. Hence, multi-intent utterances, e.g., "I need to reset the password and make a deposit from my account.", are excluded. Thirdly, to provide intent-role-based guidelines for intent reconstruction, we conduct Apriori [49] and derive the intent-role patterns, e.g., the Patterns in Fig. 2. Specifically, the extracted intentroles are fed into Apriori to obtain frequent intent-role patterns, e.g., Action-(Argument). Finally, we combine the mined concepts according to the intent-role patterns to derive the intent-slot repository. For example, as illustrated in Fig. 2, given an utterance of "Check my insurance policy", according to the obtained pattern of Action-(Argument), we can assign the concepts to it and infer the intent of "Check-(Document)" with "insurance policy" in the slot of "Document".

In the literature, there is no public dataset to be applied to verify the performance of our proposed RCAP. Though existing labeled datasets, such as ATIS [29] and SNIPS [8], have provided concise, coherent and single-sentence texts for intent detection, they are not representative for complex real-world dialogue scenarios as spoken utterances may be verbose and ungrammatical with noise and variance [40]. Hence, we collect and release a financial dataset (FinD), which consists of 2.9 million real-world Chinese utterances from nine different domains, such as insurance and financial management. Moreover, we apply RCAP learned from FinD to two new curated datasets, a public dataset in E-commerce and a human-resource dataset from a VPA, to justify the generalization of our RCAP in handling out-of-domain data.

We summarize the contributions of our work as follows:

- We define and investigate a new task in open-domain dialogue systems, i.e., automatic intent-slot induction, and propose a domain-independent tool, RCAP.
- Our RCAP can identify both coarse-grained intent-roles and abstract fine-grained concepts to automatically derive the intent-slot. The procedure can be efficiently delivered.
- More importantly, RCAP can effectively tackle the AISI task in new domains. This sheds light on the development of generalizable dialogue systems.
- We curate large-scale intent-slot annotated datasets on financial, e-commerce, and human resource and conduct experiments on the datasets to show the effectiveness of our RCAP in both in-domain and out-of-domain SLU tasks.

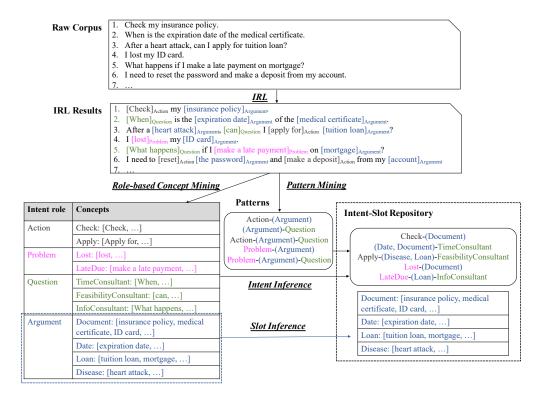


Figure 2: Flow of RCAP. The intent-role mentions and concepts are highlighted by different colors: Argument in blue, Action in gray, Problem in magenta, and Question in green. Mined concepts on each intent-role are shown in square brackets in the left-bottom table. The mined intent-role patterns are order-irrelevant. A round-bracket in Argument implies no mention or several mentions.

2 PROBLEM FORMULATION

The task of automatic intent-slot induction is defined as follows: given a set of raw utterances, $\mathcal{D} = \{u_i\}_{i=1}^M$, where M is the number of utterances in the set, $u_i = u_{i_1} \dots u_{i_{|u_i|}}$ denotes an utterance with $|u_i|$ sub-words, our goal is to derive its intent I_i for the corresponding utterance u_i . Here, we only consider one intent in one utterance, which is a typical setting of intent detection in dialogue systems [24]. Since each intent has its corresponding slots, we set the slots of I_i as $S_i = \{S_{i,1}, \dots, S_{i,\mathcal{L}_i}\}$, where \mathcal{L}_i is the number of slots in I_i and $S_{i,j}$ is a tuple with the name and value, $j = 1, \dots, \mathcal{L}_i$. It is noted that \mathcal{L}_i can be 0, implying no slot in the intent. For example, "How to get insured?" contains the intent of "Buy insurance" without a slot.

In our work, the intents are dynamically decided by the procedure of Intent Role Labeling, Concept Mining, and Intent-role Patterns Mining. S_i is also learned automatically and dynamically.

To provide a domain-independent expression of intents, we follow [23] and decompose an utterance into several key phrases with the corresponding intent-roles defined as follows:

where Action is a verb or a verb phrase, which defines an action that the user plans to take or has taken. Question delivers interrogative words or an interrogative phrase, which defines a user's intent to elicit information. Problem outlines a failure or a situation that does not meet a user's expectation. Argument expresses in nouns or noun phrases to describe the target or the holder of Action or Problem.

To further provide fine-grained semantic information for each intent-role mention, we define concepts as [5]:

Definition 2.2 (Concept). Given the extracted intent-role mentions, we can individually and independently group the mentions within each intent-role and name each cluster by a concept, an abstraction of similar instances.

To rationally combine the concepts under each intent-role and reform the user intent, we define intent-role pattern as follows:

Definition 2.3 (Intent-role Pattern). For each utterance, we decompose it into several intent-role mentions. A combination of intent-roles is defined by an intent-role pattern.

In this paper, we propose RCAP to tackle the task of AISI. Our RCAP consists of three modules: (1) intent-role labeling for recognizing the intent-roles of mentions, (2) concept mining for fine-grained concepts assignment, and (3) intent-role pattern mining to attain representative patterns. After that, we can infer the intent-slot accordingly.

3 OUR PROPOSAL

In this section, we present the implementation of the modules of our RCAP.

3.1 Intent Role Labeling (IRL)

In order to attain coarse-grained intent-roles as defined in Def. 2.1, we train an IRL model on an open-domain corpus with L annotated utterances. That is, given an utterance with m sub-words, $u = u_1 \dots u_m$, we train an IRL model to output the corresponding label, $r = r_1 \dots r_m$. Here, we apply the Beginning-Inside-Outside (BIO) schema [32] on the four intent-roles. Hence, r_i can be selected from one of the 9 tags, such as B-Action and I-Argument.

Nowadays, BERT [16] has demonstrated its superior performance on many downstream NLP tasks. We, therefore, apply it to tackle the IRL task. More specifically, given the utterance u, we can denote it by

[CLS]
$$u_1 \ldots u_m$$
 [SEP],

where [CLS] and [SEP] are two special tokens for the classification embedding and the separation embedding. u_i is the i-th subword extracted from BERT's dictionary. By applying BERT's representation, we obtain

$$h_0 h_1 \dots h_m h_{m+1}$$

where $h_i \in \mathbb{R}^d$ is the embedding of the *i*-th token, i = 0, ..., m+1 and d is the hidden size. We then apply a softmax classifier on top of the hidden features to compute the probability of each sub-word u_i to the corresponding label:

$$p(r_i|u_i) = \text{softmax}(Wh_i), \tag{2}$$

where W is the weight matrix. After that, mentions are obtained by the BI-tags on each intent-role.

3.2 Concept Mining

The goal of concept mining is to provide fine-grained labels for the determined intent-role mentions obtained in Sec. 3.1. To attain such goal, we group the mentions within the same intent-role into clusters and assign each cluster to the corresponding *concept* (see Def. 2.2) by a fine-grained label. There are two main steps: mention embeddings and mention clustering. After that, we can assign abstract fine-grained names for the clusters.

Mention Embedding This step takes the sub-word sequence of all mentions in the open domain utterances $\mathcal{D}_m^r = \{m_{kr}\}_{k=1}^{M_r}$ and outputs the embedding vector \mathbf{p}_{kr} for each mention m_{kr} , where M_r is the number of mentions in the corresponding role, $r \in \{\text{Action, Question, Argument, Problem}\}$. There are various ways to represent the intent-role mentions. To guarantee unified representations of all mentions, we do not apply BERT because its representation will change with the context. Differently, we consider the following embeddings:

- word2vec (w2v): It is a popular and effective embedding in capturing semantic meanings of sub-words. We treat intentrole mentions as integrated sub-words and represent them following the same procedure in [28].
- phrase2vec (p2v): To further include contextual features, we not only take intent-role mentions as integrated subwords but also apply phrase2vec [1], i.e., a generalization of skip-gram to learns n-gram embeddings.

- CNN embedding (CNN): To make up the insufficiency of word2-vec and phrase2vec in sacrificing semantic information inside mentions, we apply a sub-word convolutional neural network (CNN) [52] to learn better representations. That is, a CNN model takes the sequence of an input mention and outputs an embedding vector p by applying max pooling along the mention size on top of the consecutive convolution layers. The CNN embedding model is trained by skip-gram in an unsupervised manner [28]. Given mention t extracted from an utterance in the training set, we seek the embedding by minimizing the following loss for each mention c within the context of t:

$$L_p = -[\log \sigma(\mathbf{p}_c^T \mathbf{p}_t) + \sum_{i=1}^M \log \sigma(-\mathbf{p}_i^T \mathbf{p}_t)], \tag{3}$$

where σ is the sigmoid function, \mathbf{p}_t and \mathbf{p}_c are embeddings for the mention t and c, respectively. \mathbf{p}_i is the embedding of a random mention that does not occur in the context of mention t and M is the number of randomly selected mentions.

Mentions Clustering After obtaining the mention embeddings, we apply clustering on the mentions within the same intent-role to group them into corresponding concepts. In this paper, we apply the following algorithms:

- K-means [15]: It is one of the most popular clustering algorithms. However K-means algorithm needs to decide initial centroids and preset the number of clusters in advance.
- Minimum entropy (MinE) [35]: It is a famous algorithm
 by Minimizing Entropy on infomap. They apply a transition
 probability matrix to discover connected structure and have
 proved the effectiveness in community detection.
- **Label Propagation Algorithm (LPA)** [31]: It is an effective clustering algorithm and does not need to specify the number of clusters in advance. Here, we construct an $n \times n$ transition matrix T through the learned phrase embeddings, where n is the number of phrases and $T_{ij} = p_i^T p_j$ defines the inner product of two row-wise normalized vectors, p_i and p_j . To take into account the k-nearest neighbors in vector space, we only keep the top-k elements in each row of T.

Initially, we consider each phrase as a cluster and initialize Y by an identity matrix, where Y_{ij} denotes the probability that phrase i belongs to the cluster j. We then update Y by:

$$Y_t = TY_{t-1}. (4)$$

After convergence, each phrase is assigned to the cluster with the highest probability.

3.3 Intent-role Pattern Mining

To reconstruct intents from extracted intent-role mentions and concepts, we aim to explore the common patterns that people express their intents. Each pattern is a combination of intent-roles without considering the order. It is noted that by enumerating all combinations of intent-roles in Eq. (1), we can obtain 15 candidate patterns, which is computed by $\binom{4}{1} + \binom{4}{2} + \binom{4}{3} + \binom{4}{4} = 4 + 6 + 4 + 1 = 15$.

Given a large corpus with intent-roles as defined in Def. 2.1, we then apply Apriori algorithm [49], a popular frequent item set

mining algorithm, to extract the most frequent intent-role combination patterns. The corresponding parameters, such as the minimum support value and the minimum confidence value can be adjusted.

Hence, given an utterance, we apply the learned IRL model to identify the mentions with intent-roles. According to Sec. 4, we can map the mentions to appropriate concepts and determine the corresponding intent-slot based on the mined intent-role patterns.

4 INFERENCE IN SLU

In the following, we outline how to apply the learned IRL model, concepts, and intent-role patterns by our RCAP for real-world AISI tasks. Algorithm 1 outlines the procedure of inferring the intent-slot by our RCAP:

- Line 1 is to apply the learned IRL model, IRL, to extract the mentions with the corresponding intent-roles for the given utterance u. For example, given an utterance, "Check my medical report", we obtain two meaningful mention-role pairs, ("Check", Action) and ("medical report", Argument).
- Line 2 is to invoke ConInfer to assign each mention to a suitable concept within the same intent-role. Here, we first assign the concept by direct matching. ConInfer in line 6-20 lists the procedure when no exact mention appears in the concept set of M. Specifically, we compute the cosine similarity between the mention and the mentions of all concepts within the same intent-role. We then attain the concept IDs of the top-K neighbors of the mention and apply the majority vote to determine the concept. Since m = "medical report" does not appear in the mention of M, we first compute the cosine similarity between m and all mentions within Argument in M. By finding the majority concept from the top-K neighbor mentions, we assign "Document" to the concept of "medical report". If no concept is matched, we run the procedure of Concept Expansion as in Appendix A.6.
- Line 3 is to invoke ISInfer to derive the final intent-slot as defined in line 22-36. It is noted that line 25-27 is to extract multiple slots. For example, the utterance, "When is the expiration date of the medical certificate", contains multiple slots including "expiration date" and "medical certificate". An intent is then obtained by concatenating all intent-roles filled with corresponding concepts as in line 33. Hence, by filling the concept of "Check" to Action and the concept of "Document" to Argument, we obtain the intent of "Check-(Document)" for "Check my medical report" with the slot "Document" to "medical report".

5 EXPERIMENTS

In this section, we conduct experiments on the AISI task to answer the following questions:

- Q1: What is the performance of our RCAP on the AISI task for in-domain and out-of-domain datasets?
- Q2: What is the effect of each module in our RCAP and to what extend does our RCAP save human effort in the AISI task?
- Q3: What are the differences between our RCAP and traditional annotation procedure in deriving the intent-slot in real scenarios?

Algorithm 1 Online Inference.

Require: The input utterance u; the mention-concept set $S = \bigcup_{r=1}^4 S_r$, where $r \in \{\text{Action}, \text{Question}, \text{Argument}, \text{Problem}\}$, $S_r = \{\bigcup_{k_j=1}^{N_k} (m_{k_j}, r, c_k), k \in [1, M_r]\}$, M_r is the number of concepts within the intent-role r, N_k is the number of mention-concept pairs with concept c_k ; f is a phrase embedding function; δ is a parameter to filter out dissimilar mentions; K is the number of nearest neighbors; the pattern set \mathcal{P} .

```
number of nearest neighbors; the pattern set \mathcal{P}.
Ensure: The set of intent-role mentions with concept ID, Result;
  1: \{(m_1, r_1), \cdots, (m_N, r_N)\} \leftarrow IRL(\mathbf{u})
  2: \{c_1, \ldots, c_N\} \leftarrow \text{ConInfer}(\{(m_1, r_1), \cdots, (m_N, r_N)\}, \mathcal{S}, \delta, K)
 3: (I,S) \leftarrow \text{ISInfer}(\{(m_1,r_1,c_1),\cdots,(m_N,r_N,c_N)\},\mathcal{P})
  4: return (I, S)
 5: Function ConInfer(\{(m_1, r_1), \cdots, (m_N, r_N)\}, S, \delta, K)
 6: Result = \{\}
 7: for j = 1; j \le N; j ++ do
        Tuple = \{\}
        for all (m_i, r_j, c_x) in S_{r_j}, x is its concept ID do
 10:
           sim = cos(f(m_j), f(m_i))
           if sim > \delta then
 11:
              Tuple = Tuple \cup \{(sim, x)\}
 12:
           end if
 13:
        end for
 14:
        Tuple_o \leftarrow Sort Tuple by sim with decreasing order
        Get the concept ID list: ID_{topK} = Tuple_o[0:K]
 16:
        Find the majority concept ID q_o in set ID_{topK}
        Result = Result \cup \{q_o\}
 19: end for
 20: return Result
 21: EndFunction
 22: Function ISInfer(\{(m_1, r_1, c_1), \cdots, (m_N, r_N, c_N)\}, \mathcal{P})
 23: Dict = \{\}, Slot = \{\}
 24: for j = 1; j \le N; j + + do
 25:
        if r_i == Argument then
 26:
           SlotD[c_i] = SlotD[c_i] + \{m_i\}
        Dict[r_i] = Dict[r_i] + \{c_i\}
 29: end for
 30: p = [\mathbf{for} \ v \ \text{in} \ \mathcal{P} \ \mathbf{do} \ \mathbf{if} \ \text{set}(Dict.keys) == \text{set}(v)]
 31: Intent = []
 32: for r in p do
        Intent \leftarrow Intent + '-' + Dict[r]
 34: end for
 35: return (Intent, SlotD)
```

5.1 Experiment Setup

36: EndFunction

Data We curate a financial dataset (FinD) with 2.9 million real-world utterances collected from a financial VPA in 9 domains. We additionally construct a test set of 1,500 annotated utterances by five domain experts with an inter-annotator agreement of the Fleiss' Kappa larger than 0.75.

Table 1: Statistics of the curated datasets

Data	Domain name	No. of utter. b	i./m./a. ^a utter. len.	Vocab / domain	No. of I/S ^c
	Insurance	1,008,682	5/14/975	4,937	1,179/53
	Fin. Mgmt.	851,537	5/14/999	5,074	705/45
	APP Ops.	311,373	5/15/980	4,267	969/39
_	Banking	263,458	5/14/852	3,989	578/50
FinD	User Info.	231,982	5/13/770	3,999	419/44
H	Health	122,385	5/15/984	3,795	126/23
	Reward Pts.	35,556	5/15/998	3,112	279/15
	RE & Vehicle	9,741	5/13/398	2,111	109/11
	Others	133,959	5/13/624	3,564	669/49
	Commodity	342,231	5/14/168	2,189	356/28
ECD	Logistics	98,720	5/13/228	1,825	229/26
団	Post-sale	29,616	5/17/295	1,941	116/25
HRD	Career	64,559	5/14/624	4,206	341/43

 $[^]a$: i./m./a. is equivalent to minimum/average/maximum.

Table 2: Statistics in the test sets

Data	No. of domains	i./m./a. ^a utter. ^b	i./m./a. ^a utter. len.	Vocab	No. of I/S ^c
FinD	9	2/167/908	5/11/25	667	178/39
ECD	3	330/500/604	5/9/24	562	90/27
HRD	1	1500	5/10/27	606	121/31

a: i./m./a. is equivalent to minimum/average/maximum.

Moreover, to justify the generalization ability of our RCAP, we apply the learned IRL model, concepts, and patterns from FinD to evaluate the model performance on two out-of-domain datasets: a large-scale public Chinese conversation corpus in E-commerce (ECD) [53] with the domains of Commodity, Logistics, and Postsale, and a human resource dataset (HRD) collected from a human resource VPA. Similarly, we annotate additional 1,500 utterances of each dataset as the test sets. The detailed statistics of the curated datasets and the test sets are reported in Table 1 and Table 2, respectively.

Compared Methods We compare the following methods:

- POS: Ansj¹, a popular tool for Chinese terminologies segmentation, is first applied to determine the intent-role labels and then derive the corresponding intent-slot following *ConInfer* and *ISInfer* in Algo. 1.
- DP: a dependency parsing toolbox developed by LTP² is applied to determine the intent-role labels and then derive the corresponding intent-slot following *ConInfer* and *ISInfer* in Algo. 1. Both labels in POS and DP can not be directly applied for IRL tasks. Therefore, we design some rules to

- map POS tags and DP labels to IRL labels (see more details in Appendix A.2).
- Joint-BERT [3]: a strong supervised model is trained with a Joint-BERT model on another 3.5k annotated utterances by two domain experts to derive the corresponding 48 predefined intents and 43 predefined slots. In the out-of-domain datasets, we include the intent of "others" for out-of-schema utterances. It is noted that the number of labeled utterances is sufficient to train good performance; see more results in Appendix A.1.
- RCAP: our proposed RCAP applies a BERT model defined in Eq. (2) to derive the intent-role labels, CNN embedding with LPA for concept mining, and the Apriori algorithm for pattern mining.
- RCAP+refine: the grouped mentions of our RCAP are manually refined by domain experts to pick out outliers and merge them into new concepts based on experts' experience.

Training Details In training the IRL model, we fine-tune the BERTbase ³ model on 6,000 annotated utterances of FinD in 30 epochs by the following settings: a mini-batch size of 32, a maximum sequence length of 128, and a learning rate of 2×10^{-5} . For training the CNN embeddings, we leverage TensorFlow implementation of word2vec with CNN on empirically-set common parameters, such as filter windows of 1, 2, 3, 4 with 32 feature maps each, word2vec dimension of 128. The maximum length of each mention is 16. The size of the skip window, i.e., the number of sub-words to consider to the left and right of the current sub-words, is 2. The skip number, i.e., the number of times to reuse an input to generate a labels, is 2. The sampled number, i.e., the number of negative examples is 64. For clustering, the number of nearest neighbors in LPA is empirically set to 5. K is 100 for K-means to attain the best performance. In intent-role pattern mining, the minimum support value is set to 0.05 and the minimum confidence value is 0.1 for the Apriori algorithm. In ConInfer, δ is set to 0.2 and K = 5.

Evaluation Metrics In the experiment, following [22], we apply Macro-F1 to evaluate the performance of intent-role detection and the standard metrics, precision, recall, and F1, to measure the performance of slot filling. Here, we adopt v-measure, a comprehensive measurement of both homogeneity and completeness [50], which ranges in 0 to 1, to evaluate the clustering performance. The larger the v-measure score, the better the clustering result is.

5.2 Performance on AISI

Table 3 reports the performance of the model trained on FinD and evaluations on all the three test sets to answer **Q1**. The results on FinD are to report the in-domain performance while the results on ECD and HRD are to evaluate the out-of-domain performance. We have the following observations:

- RCAP significantly outperforms the baselines, POS and DP, on all three datasets under the paired t-test (p < 0.05). The results make sense because POS and DP perform poor in the task of IRL; see more IRL results in Table 4.
- RCAP attains competitive performance to the strong supervised method, Joint-BERT, on FinD. The results demonstrate the effectiveness of RCAP in handling in-domain SLU. More

b: utter. denotes utterances.

c: I/S denotes intents and slots.

b: utter. denotes utterances.

 $[^]c$: I/S denotes intents and slots.

¹https://github.com/NLPchina/ansj_seg

²https://www.ltp-cloud.com

³https://github.com/google-research/bert

Dataset	In-domain FinD		Out-of-domain			
Dataset			ECD		HRD	
Approach	Intent P/R/F1	Slot P/R/F1	Intent P/R/F1	Slot P/R/F1	Intent P/R/F1	Slot P/R/F1
POS	0.34/0.35/0.34	0.49/0.50/0.49	0.19/0.20/0.19	0.56/0.45/0.50	0.05/0.05/0.05	0.27/0.40/0.32
DP	0.48/0.49/0.48	0.51/0.79/0.62	0.45/0.46/0.45	0.60/0.56/0.58	0.28/0.28/0.28	0.61/0.41/0.49
Joint-BERT	0.89/0.89/0.89	0.92/0.90/0.91	0.19/0.21/0.20	0.49/0.64/0.55	0.02/0.02/0.02	0.42/0.33/0.37
RCAP	0.82/0.84/0.83	0.85/0.89/0.87	0.79/0.80/0.79	0.85/0.79/0.82	0.75/0.76/0.75	0.84/0.74/0.79
RCAP + refine	0.91/0.90/0.90	0.92/0.91/0.92	0.85/0.86/0.85	0.85/0.81/0.83	0.90/0.91/0.90	0.86/0.75/0.80

Table 3: Compared results on in-domain and out-of-domain SLU datasets.

Table 4: Compared results on IRL performance in FinD shown by Precision/Recall/F1.

	Action	Problem	Question	
POS	0.13/0.30/0.18	0.02/0.01/0.01	0.32/0.13/0.18	
DP	0.58/0.48/0.53	0.51/0.56/0.53	0.83/0.56/0.67	
RCAP	0.86/0.87/0.87	0.88/0.83/0.85	0.94/0.93/0.93	
	Argument	Ove	rall	
POS	0.21/0.24/0.22	0.18/0.	20/0.19	
DP	0.74/0.49/0.59	0.68/0.51/0.58		
RCAP	0.92/0.91/0.92	0.91/0.	90/0.90	

significantly, RCAP can easily transfer to other domains and achieves the best performance in ECD and HRD. On the contrary, Joint-BERT performs poorly, even worse than POS and DP, in ECD and HRD. This is because Joint-BERT does not learn the semantic features in new utterances and may assign the out-of-schema utterances to wrong intents.

- By examining the results on the out-of-domain datasets, RCAP attains at least 76% higher F1-score on intent detection and 41% higher F1-score on slot filling than the best baseline. This implies that RCAP can effectively infer out-of-domain intent-slot.
- RCAP after refinement achieves the best performance, 0.9
 Macro-F1 score in intent detection and 0.92 F1-score in slot filling on FinD. More importantly, the superior performance can be retained in ECD and HRD. The results show that the refinement can gain 8.4%-20.0% improvement on intent detection and 1.3%-5.7% improvement on slot filling.

5.3 Drill-down Analysis

In the following, we analyze the effect of each module in RCAP and the schema induction efficiency to answer **Q2**.

IRL Performance IRL is a crucial step to the success of RCAP. Here, we evaluate the performance, i.e., precision, recall, and F1-score, on identifying the intent-role labels of utterances and report the performance on sub-words level. **Overall** shows a weighted score of the corresponding score on all intent-roles. To provide references, we compare RCAP with the baselines, POS and DP. Since Joint-BERT cannot provide the intent-role labels, we do not report its result here.

Table 4 reports the performance of compared methods and shows the following observations:

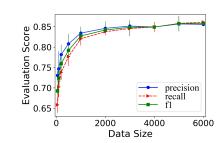


Figure 3: Performance of IRL models trained with different number of training data.

- RCAP by utilizing BERT significantly outperforms POS and DP in intent-role labeling. POS and DP perform poorly and attain only 0.19 and 0.58 on overall F1-scores on FinD. This implies that it is non-trivial to determine the intent-roles.
- By examining the performance on each role, we observe that the F1-scores in Action and Problem are slightly lower than those in Question and Argument. A reason is that the mentions in both Action and Problem contain verbs or verb phrases, which leads to more errors in predicting the roles. Our trained BERT model can still achieve competitive performance, i.e., 0.87 and 0.85 F1-score, on Action and Problem, respectively.

Effect of the number of annotated data in IRL Here, we argue that to attain satisfactory IRL performance, our RCAP only needs to annotate a small number of utterances. To support this argument, we ask three domain experts to annotate 6,500 utterances with around 15K mention-role pairs. In the test, to mimic the real-world scenarios, we keep all utterances without eliminating those with multiple intents or with only Argument. This makes the test set slightly different from Table 2. In the test, we hold 500 annotated utterances for test while varying the number of training samples in {50, 100, 200, 500, 1,000, 2,000, 3,000, 4,000, 5,000, 6,000}. Figure 3 shows the total performance of precision, recall, and F1 scores on the sub-word level for all intent roles. The results show that when the number of training data reaches 2,000, F1 converges to 0.85, which corresponds to 0.9 in Table 4. The slightly worse performance in Fig. 3 than that in Table 4 comes from the broader types of utterances in the test set. Overall, we only need to annotate around 2,000 utterance to attain satisfactory IRL performance, which indicates very light labeling effort.

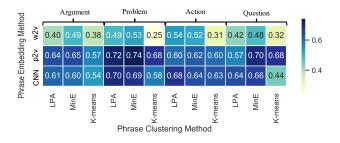


Figure 4: Intent-role mention clustering performance.

Effect of Concept Mining We test three mention embedding methods and three clustering algorithms as described in Sec. 3.2, on all 2.9 million utterances in FinD. We then extract around 10,000 frequent intent-role mentions for evaluations. The clustering results in Fig. 4 implies that:

- Among the three mention embedding methods, phrase2vec and CNN significantly outperform words2vec while CNN performs slightly better than phrase2vec. We conjecture that phrase2vec have effectively absorbed the contextual information for the mentions and CNN embeddings can capture semantic information for the words inside mentions.
- Among the three clustering methods, LPA and MinE significantly outperform K-means while LPA is slightly better than MinE. We believe that both LPA and MinE capture the structure of the data and contain higher tolerance on embedding errors. On the contrary, K-means may converge to a local minimum and heavily rely on the initial state.
- The results show that by applying the mention embedding method of phrase2vec or CNN embedding and the clustering algorithm of LPA or MinE, we can yield satisfactory v-measure scores, i.e., in the range of 0.6 to 0.8. For other metrics, we also obtain similar observations; see more results on Homogeneity and Completeness in Appendix A.3.

Results of Intent-role Pattern Mining By applying the Apriori algorithm, we can obtain totally 10 patterns written into 5 typical patterns as shown in the results of Pattern Mining in Fig. 2, Action-(Argument), (Argument)-Question, Action-(Argument)-Question, Problem-(Argument), and Problem-(Argument)-Question, where Argument may not appear in the patterns. For example, the patterns of Action-(Argument) and Action-Question-(Argument) also include the patterns of Action and Action-Question without Argument, respectively. These patterns can cover over 70% of utterances in FinD. The remaining utterances consist of multiple intents or chitchats without explicit intents, which are not the targeted cases in this paper.

Performance of Concept Inference We test the performance of *ConInfer* in Algo. 1. Since frequently-appeared mentions usually can be directly mapped to the corresponding concepts, to test the performance in long-tail situations, we additionally collect 1,000 utterances from FinD. Each utterance contains at least one low-frequent mention, i.e., appearing less than 20 times in the dataset. We obtain an inference accuracy of 0.88 on this set, which implies the robustness of our RCAP in concept inference.

Table 5: Schema induction performance.

	Intents	Slots	Time (hours)
MANUAL	7	16	24
RCAP	16	16	2

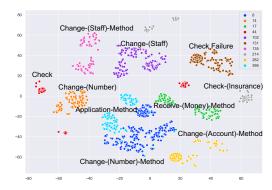


Figure 5: Visualizing the clustering arrangement for utterances belonging to ten intents in FinD, where different colors denote different intents.

Efficiency We compare the time cost of traditional manual-schema induction and our RCAP. We ask a domain expert in "Health" domain to derive a schema by the following common schema induction steps: 1) selecting utterances in the "Health" domain; 2) grouping similar utterances and abstracting them into intents; 3) enumerating slots for each intent; 4) repeating step 2) and 3) to construct the schema. In comparison, another expert only needs to determine whether the derived intent-slot labels by our RCAP lie in the "Health" domain. Since utterances with the same intents may be sparsely distributed in the corpus, the schema induction may be extremely difficult and time consuming. As shown in Table 5, it takes the first domain expert about 24 hours to manually derive only 7 intents and 16 corresponding slots. On the contrary, our RCAP can automatically group utterances of the same intents. The other expert can, therefore, take only 3 hours to produce a similar schema with 9 additional intents; see more results in Appendix A.5.

5.4 Case Studies

We now present the qualitative evaluation of our RCAP to answer Q3. To show RCAP's ability to conflate different utterances into the same or similar intent category, we concatenate the intent-role mention embeddings of each utterance and plot them by t-SNE in a 2D-space. Fig. 5 shows that the utterances with the same intents (representing by the same colors) cluster in compact groups. For example, the utterances of "I want to change my sales manager." and "Change another representative" are grouped into the intent of "Change-(Staff)" in purple, while the utterances of "How can I have another customer service representative?" and "What are the ways to replace my current sales manager" are grouped into the intent

Table 6: Fine-grained intents discovered by RCAP vs. manually mined intents for eight cases from FinD.

Utterances	RCAP	Manual
What materials I need to in-	(Loan Application) – Doc-	Loan Applica-
clude to loan application	ument Consultant	tion
When will the mortgage ar-	Arrival-(Loan,Time)-	
rive?	Consultant	
My bank loan was rejected.	Refused-(Loan)	
Can I change the insured of	Replace-(Insured)-	Insurance
this car insurance?	Feasibility	Info Modifica-
		tion
Change the policyholder	Replace-(Policyholder)	
What is the weather today?	(Weather,Date)-Inquiry	Others
The problem I reported was	Not solved-(Issue)	
not solved.		
Call the bank customer ser-	Contact-(Customer Ser-	
vice.	vice)	

of "Change-(Staff)-Method" in pink. Due to their similar semantic meanings, both intents lie close to each other in Fig. 5. This implies that our RCAP can effectively group similar utterances into same intents and separate different intents.

Table 6 lists the manual annotation and our RCAP on eight utterances. Our RCAP can provide more detailed intents comparing with the manual annotated results. Moreover, our RCAP can induce specific intents for long-tailed utterances. On the contrary, manual annotation usually assigns them to the intent of *Others*.

In conclusion, concepts produced by RCAP can help unify utterances with similar semantic meanings into the same intents. Besides, the detected intents contain fine-grained information and can help induce a meaningful schema, which can cover long-tail utterances.

6 RELATED WORK

Spoken Language Understanding The main goal of an SLU component is to convert the spoken language into structural semantic forms that can be used to generate response in dialogue systems [5]. SLU contains two main sub-tasks: intent classification, which can be treated as a multi-label classification task [14, 19, 33], and slot filling, which can be treated as a sequence labeling task [21, 26, 27]. Recently, joint models for intent detection and slot filling [3, 12, 13, 24, 30, 48, 51] have received more attention since information in intent labels can further guide the slot filling task. The above approaches require predefined intent-slot schemas and huge labeled data annotated by domain experts to attain good performance. To alleviate the limits, Vedula et al. [43] identify domain-independent actions and objects, and construct intents on them. However, their methods extracted intents that are restricted in action-object form, and cannot fill in slots. This motivates us to explore automatic intent-slot induction in broader scenarios.

Intent-Slot induction Traditional SLU systems rely heavily on domain experts to enumerate intent-slot schemas, which may be limited and bias the subsequent data collection [5]. Hence, many works propose approaches for automatic intent detection. For example, Xia et al. [47] propose a zero-shot intent classification model

to detect un-seen intents. Their work is useful for similar domain transfer, but not valid for new domains. Kim and Kim [17], Lin and Xu [22] can only detect if an utterance contains out-of-domain intents. Unsupervised approaches [5, 6, 36, 41, 42] have been proposed to build models for slot induction and filling. These papers have applied clustering algorithms to group concepts. However, their performance still rely on the corresponding domains. To address this issue, we investigate unsupervised domain-independent methods for both intent and slot.

7 CONCLUSION

In this paper, we define and explore a new task of automatic intentslot induction. We then propose a domain-independent approach, RCAP, which can cover diverse utterances with strong flexibility. More importantly, our RCAP can be effectively transferred to new domains and sheds light on the development of generalizable dialogue systems. Extensive experiments on real-word datasets show that our RCAP produces satisfactory SLU results without manuallylabeled intent-slot and outperforms strong baselines. As for the out-of-domain datasets, our RCAP can gain great improvement than the best baseline. Besides, RCAP can significantly reduce the human effort in intent-slot schema induction and help to discover new or unseen intent-slot with fine-grained details. Several promising future directions can be considered: (1) extending the singleintent induction to multi-intents induction; (2) utilizing external well-defined knowledge graph to fine-tune the mined concepts; (3) developing a generalizable dialogue systems based on our RCAP.

ACKNOWLEDGMENTS

The authors are grateful to the anonymous reviewers for their insightful feedback, to Xuan Li for helpful discussions during the course of this research. We are also immensely grateful to Bingfeng Luo and Kunfeng Lai for their comments and help on an earlier version of the manuscript.

REFERENCES

- Mikel Artetxe, Gorka Labaka, and Eneko Agirre. 2018. Unsupervised Statistical Machine Translation. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing. 3632–3642.
- [2] Hongshen Chen, Xiaorui Liu, Dawei Yin, and Jiliang Tang. 2017. A survey on dialogue systems: Recent advances and new frontiers. Acm Sigkdd Explorations Newsletter 19, 2 (2017), 25–35.
- [3] Qian Chen, Zhu Zhuo, and Wen Wang. 2019. BERT for Joint Intent Classification and Slot Filling. arXiv preprint arXiv:1902.10909 (2019).
- [4] Yun-Nung Chen, Asli Celikyilmaz, and Dilek Hakkani-Tur. 2018. Deep learning for dialogue systems. In Proceedings of the 27th International Conference on Computational Linguistics: Tutorial Abstracts. 25–31.
- [5] Yun-Nung Chen, William Yang Wang, and Alexander I Rudnicky. 2013. Unsupervised induction and filling of semantic slots for spoken dialogue systems using frame-semantic parsing. In 2013 IEEE Workshop on Automatic Speech Recognition and Understanding. IEEE, 120–125.
- [6] Yun-Nung Chen, William Yang Wang, and Alexander I Rudnicky. 2014. Leveraging frame semantics and distributional semantics for unsupervised semantic slot induction in spoken dialogue systems. In 2014 IEEE Spoken Language Technology Workshop (SLT). IEEE, 584–589.
- [7] Zhiyuan Chen, Bing Liu, Meichun Hsu, Malu Castellanos, and Riddhiman Ghosh. 2013. Identifying Intention Posts in Discussion Forums. In Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. Association for Computational Linguistics, Atlanta, Georgia, 1041–1050. https://www.aclweb.org/anthology/N13-1124
- [8] Alice Coucke, Alaa Saade, Adrien Ball, Théodore Bluche, Alexandre Caulier, David Leroy, Clément Doumouro, Thibault Gisselbrecht, Francesco Caltagirone, Thibaut Lavril, et al. 2018. Snips voice platform: an embedded spoken language

- understanding system for private-by-design voice interfaces. arXiv preprint arXiv:1805.10190 (2018).
- [9] Marco Damonte, Rahul Goel, and Tagyoung Chung. 2019. Practical Semantic Parsing for Spoken Language Understanding. In NAACL-HLT. 16–23. https://doi.org/10.18653/v1/n19-2003
- [10] Andrea Di Sorbo, Sebastiano Panichella, Corrado A Visaggio, Massimiliano Di Penta, Gerardo Canfora, and Harald C Gall. 2015. Development emails content analyzer: Intention mining in developer discussions (T). In 2015 30th IEEE/ACM International Conference on Automated Software Engineering (ASE). IEEE, 12–23.
- [11] Chih-Wen Goo, Guang Gao, Yun-Kai Hsu, Chih-Li Huo, Tsung-Chieh Chen, Keng-Wei Hsu, and Yun-Nung Chen. 2018. Slot-Gated Modeling for Joint Slot Filling and Intent Prediction. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers). Association for Computational Linguistics, New Orleans, Louisiana, 753–757. https://doi.org/10.18653/v1/N18-2118
- [12] Chih-Wen Goo, Guang Gao, Yun-Kai Hsu, Chih-Li Huo, Tsung-Chieh Chen, Keng-Wei Hsu, and Yun-Nung Chen. 2018. Slot-gated modeling for joint slot filling and intent prediction. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers). 753–757.
- [13] Daniel Guo, Gokhan Tur, Wen-tau Yih, and Geoffrey Zweig. 2014. Joint semantic utterance classification and slot filling with recursive neural networks. In 2014 IEEE Spoken Language Technology Workshop (SLT). IEEE, 554–559.
- [14] Homa B Hashemi, Amir Asiaee, and Reiner Kraft. 2016. Query intent detection using convolutional neural networks. In *International Conference on Web Search* and Data Mining, Workshop on Query Understanding.
- [15] Tapas Kanungo, David M Mount, Nathan S Netanyahu, Christine D Piatko, Ruth Silverman, and Angela Y Wu. 2002. An efficient k-means clustering algorithm: Analysis and implementation. *IEEE transactions on pattern analysis and machine* intelligence 24, 7 (2002), 881–892.
- [16] Jacob Devlin Ming-Wei Chang Kenton and Lee Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In Proceedings of NAACL-HLT. 4171–4186.
- [17] Joo-Kyung Kim and Young-Bum Kim. 2018. Joint Learning of Domain Classification and Out-of-Domain Detection with Dynamic Class Weighting for Satisficing False Acceptance Rates. *Proc. Interspeech 2018* (2018), 556–560.
 [18] Joo-Kyung Kim, Gokhan Tur, Asli Celikyilmaz, Bin Cao, and Ye-Yi Wang. 2016.
- [18] Joo-Kyung Kim, Gokhan Tur, Asli Celikyilmaz, Bin Cao, and Ye-Yi Wang. 2016. Intent detection using semantically enriched word embeddings. In 2016 IEEE Spoken Language Technology Workshop (SLT). IEEE, 414–419.
- [19] Young-Bum Kim, Sungjin Lee, and Karl Stratos. 2017. Onenet: Joint domain, intent, slot prediction for spoken language understanding. In 2017 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU). IEEE, 547–553.
- [20] Thomas Kollar, Danielle Berry, Lauren Stuart, Karolina Owczarzak, Tagyoung Chung, Lambert Mathias, Michael Kayser, Bradford Snow, and Spyros Matsoukas. 2018. The alexa meaning representation language. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 3 (Industry Papers). 177–184.
- [21] Gakuto Kurata, Bing Xiang, Bowen Zhou, and Mo Yu. 2016. Leveraging Sentence-level Information with Encoder LSTM for Semantic Slot Filling. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, Austin, Texas, 2077–2083. https://doi.org/10.18653/v1/D16-1223
- [22] Ting-En Lin and Hua Xu. 2019. Deep Unknown Intent Detection with Margin Loss. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics. 5491–5496.
- [23] Bing Liu. 2020. Sentiment analysis: Mining opinions, sentiments, and emotions. Cambridge university press.
- [24] Bing Liu and Ian Lane. 2016. Attention-Based Recurrent Neural Network Models for Joint Intent Detection and Slot Filling. Interspeech 2016 (2016), 685–689.
- [25] Zihan Liu, Genta Indra Winata, Peng Xu, and Pascale Fung. 2020. Coach: A Coarse-to-Fine Approach for Cross-domain Slot Filling. In ACL. 19–25. https://www.aclweb.org/anthology/2020.acl-main.3/
- [26] Grégoire Mesnil, Yann Dauphin, Kaisheng Yao, Yoshua Bengio, Li Deng, Dilek Hakkani-Tur, Xiaodong He, Larry Heck, Gokhan Tur, Dong Yu, et al. 2014. Using recurrent neural networks for slot filling in spoken language understanding. IEEE/ACM Transactions on Audio, Speech, and Language Processing 23, 3 (2014), 530–539.
- [27] Grégoire Mesnil, Xiaodong He, Li Deng, and Yoshua Bengio. 2013. Investigation of recurrent-neural-network architectures and learning methods for spoken language understanding.. In *Interspeech*. 3771–3775.
- [28] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781 (2013)
- [29] Patti Price. 1990. Evaluation of spoken language systems: The ATIS domain. In Speech and Natural Language: Proceedings of a Workshop Held at Hidden Valley, Pennsylvania, June 24-27, 1990.
- [30] Libo Qin, Wanxiang Che, Yangming Li, Haoyang Wen, and Ting Liu. 2019. A Stack-Propagation Framework with Token-Level Intent Detection for Spoken

- Language Understanding. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP). 2078–2087.
- [31] Usha Nandini Raghavan, Réka Albert, and Soundar Kumara. 2007. Near linear time algorithm to detect community structures in large-scale networks. *Physical review E* 76, 3 (2007), 036106.
- [32] Lance A Ramshaw and Mitchell P Marcus. 1999. Text chunking using transformation-based learning. In Natural language processing using very large corpora. Springer, 157–176.
- [33] Suman Ravuri and Andreas Stoicke. 2015. A comparative study of neural network models for lexical intent classification. In 2015 IEEE Workshop on Automatic Speech Recognition and Understanding (ASRU). IEEE, 368–374.
- [34] Andrew Rosenberg and Julia Hirschberg. 2007. V-measure: A conditional entropy-based external cluster evaluation measure. In Proceedings of the 2007 joint conference on empirical methods in natural language processing and computational natural language learning (EMNLP-CoNLL). 410–420.
- [35] Martin Rosvall and Carl T Bergstrom. 2008. Maps of random walks on complex networks reveal community structure. Proceedings of the National Academy of Sciences 105, 4 (2008), 1118–1123.
- [36] Chen Shi, Qi Chen, Lei Sha, Sujian Li, Xu Sun, Houfeng Wang, and Lintao Zhang. 2018. Auto-Dialabel: Labeling Dialogue Data with Unsupervised Learning. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, Brussels, Belgium, 684–689. https://doi.org/10.18653/v1/D18-1072
- [37] Lucien Tesnière. 1959. Eléments de syntaxe structurale. (1959).
- [38] David S Touretzky, Michael C Mozer, and Michael E Hasselmo. 1996. Advances in Neural Information Processing Systems 8: Proceedings of the 1995 Conference. Vol. 8. Mit Press.
- [39] Gokhan Tur and Renato De Mori. 2011. Spoken language understanding: Systems for extracting semantic information from speech. John Wiley & Sons.
- [40] Gokhan Tur, Dilek Hakkani-Tür, and Larry Heck. 2010. What is left to be understood in ATIS?. In 2010 IEEE Spoken Language Technology Workshop. IEEE, 19–24.
- [41] Gokhan Tur, Dilek Hakkani-Tür, Dustin Hillard, and Asli Celikyilmaz. 2011. Towards unsupervised spoken language understanding: Exploiting query click logs for slot filling. In Twelfth Annual Conference of the International Speech Communication Association.
- [42] Gokhan Tur, Minwoo Jeong, Ye-Yi Wang, Dilek Hakkani-Tür, and Larry Heck. 2012. Exploiting the semantic web for unsupervised natural language semantic parsing. In Thirteenth Annual Conference of the International Speech Communication Association.
- [43] Nikhita Vedula, Nedim Lipka, Pranav Maneriker, and Srinivasan Parthasarathy. 2020. Open Intent Extraction from Natural Language Interactions. In *Proceedings* of The Web Conference 2020. 2009–2020.
- [44] William Yang Wang, Dan Bohus, Ece Kamar, and Eric Horvitz. 2012. Crowdsourcing the acquisition of natural language corpora: Methods and observations. In 2012 IEEE Spoken Language Technology Workshop (SLT). IEEE, 73–78.
- [45] TH Wen, D Vandyke, N Mrkšíc, M Gašíc, LM Rojas-Barahona, PH Su, S Ultes, and S Young. 2017. A network-based end-to-end trainable task-oriented dialogue system. In 15th Conference of the European Chapter of the Association for Computational Linguistics, EACL 2017-Proceedings of Conference, Vol. 1. 438–449.
- [46] Ryen W White, Matthew Richardson, and Wen-tau Yih. 2015. Questions vs. queries in informational search tasks. In Proceedings of the 24th International Conference on World Wide Web. 135–136.
- [47] Congying Xia, Chenwei Zhang, Xiaohui Yan, Yi Chang, and Philip Yu. 2018. Zero-shot User Intent Detection via Capsule Neural Networks. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, Brussels, Belgium, 3090–3099. https://doi.org/10.18653/v1/D18-1348
- [48] Puyang Xu and Ruhi Sarikaya. 2013. Convolutional neural network based triangular crf for joint intent detection and slot filling. In 2013 ieee workshop on automatic speech recognition and understanding. IEEE, 78–83.
- [49] Jiao Yabing. 2013. Research of an improved apriori algorithm in data mining association rules. *International Journal of Computer and Communication Engineering* 2, 1 (2013), 25.
- [50] Jianhua Yin and Jianyong Wang. 2014. A dirichlet multinomial mixture model-based approach for short text clustering. In Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining. 233–242.
- [51] Xiaodong Zhang and Houfeng Wang. 2016. A joint model of intent determination and slot filling for spoken language understanding. In Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence. 2993–2999.
- [52] Xiang Zhang, Junbo Zhao, and Yann LeCun. 2015. Character-level Convolutional Networks for Text Classification. Advances in Neural Information Processing Systems 28 (2015), 649–657.
- [53] Zhuosheng Zhang, Jiangtong Li, Pengfei Zhu, Hai Zhao, and Gongshen Liu. 2018. Modeling Multi-turn Conversation with Deep Utterance Aggregation. In Proceedings of the 27th International Conference on Computational Linguistics. 3740–3752.

A APPENDIX

A.1 Vary Training Data Size for Joint-BERT

In this section, we quantify the annotation requirements for the Joint-BERT model for SLU tasks. We randomly select 5,000 utterances from FinD, and annotate them with intent-slot for test. In the test, we hold on additional 1,500 annotated utterances for test while varying the number of training samples in {150, 300, 500, 1,000, 1,500, 2,500, 3,000, 3,500}. Figure 6 shows the performance of Joint-BERT in intent detection (blue line) and slot filling (red) on different number of training samples. F1-score is used for evaluations. The results show that the F1-scores for intent and slot converge to 0.89 and 0.91 when the data size reaches 2,500. This implies that to train Joint-BERT with good performance, we usually need around 2,500 annotated utterance.

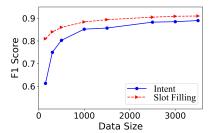


Figure 6: Performance of the Joint-BERT model trained on different number of training data, including intent detection (blue) and slot filling (red).

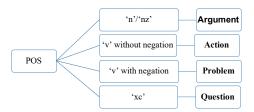


Figure 7: Mapping rules from POS tags to IRL intent-role labels.

A.2 IRL training Details

We provide more training details for IRL, including POS, DP, and our RCAP.

- POS: Based on the tags generated by POS, we write a set of rules to derive the corresponding intent-slot labels as in Fig. 7:
 - A noun or noun phrase is set as Argument;
 - A verb or verb phrase without negation words is set as Action;
 - $\ \ A \ verb \ or \ verb \ phrase \ with \ negation \ words \ is \ set \ as \ {\tt Problem};$
 - An interrogative word or phrase is set as Question.

(a)			(b)		(c)
Query	Label	Query	Label	Query	Label
你	0	取	B-action	账	B-Argument
好	0	消	I-action	户	I-Argument
生	B-Argument	刚	0	转	I-Argument
存	I-Argument	才	0	出	I-Argument
金	I-Argument	的	0	提	B-problem
可	B-question	贷	B-Argument	示	I-problem
以	B-question	款	I-Argument	交	I-problem
抵	B-action	申	I-Argument	易	I-problem
交	I-action	请	I-Argument	失	I-problem
保	B-Argument			败	I-problem
费	I-Argument			,	0
吗	B-question			怎	B-question
?	I-question			么	I-question
				办	I-question

Figure 8: Three IRL results: (a) Hi, can the survival benefit pay the premium? (b) Cancel the loan application (c) Account transfer transaction failed, what should I do. The Query columns are sub-words of input utterances to the IRL labeling model, the Label columns are outputs by RCAP. "B" indicates the beginning tag, "I" indicates the inside tag, and "O" indicates the outside tag.

- DP: We first use DP on each utterance to generate parsing results with corresponding labels. Afterwards, mention-concept sets mined by RCAP are utilized to decide the intentrole for each mention.
 - lies in Action mentions and labeled as "HED" or "COO" is set as Action;
 - lies in Problem mentions and labeled as "HED" or "COO" is set as Problem;
 - lies in Argument mentions and has dependency relations to Action or Problem is set as Argument;
 - lies in Question mentions and has dependency relations to Action or Problem is set as Question.

A.3 Clustering Performance

We introduce the other two metrics to evaluate the performance of intent-role mention clustering in experiments: homogeneity and completeness. Homogeneity and completeness are entropy-based measures that are symmetrical to each other. A clustering result satisfies prefect homogeneity if the class distribution with each cluster is skewed to a single class. A clustering result satisfies perfect completeness if all datapoints that are members of a single class are clustered to a single cluster [34]. V-measure used in Sec. 5.3 is a comprehensive measurement of both homogeneity and completeness [50]. Fig. 10 shows the clustering performance on all intent-roles using homogeneity and completeness.

A.4 Samples in Concept Repository

In elucidating the concept repository produced by concept mining, we show some samples for all different intent-roles as in Fig. 9.

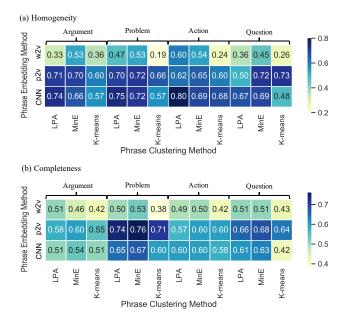


Figure 10: Intent-role mention clustering evaluations on all intent-roles using (a) completeness and (b) homogeneity, with different mention embedding methods and clustering algorithms included. The color bar shows evaluation scores decrease from dark blue to light yellow.

UTTERANCES	MANUAL	RCAP
How to claim for whom diagnosed with hypertension?	Disease related claim: procedure	Claim-(Disease)-Method
Can I claim for heart disease?	Disease related claim: feasibility	Claim-(Disease)-Feasibility
What is the waiting period to claim for cancer patient?	Disease related claim: waiting period	Claim-(Disease, Waiting Period)
How much can I get if I claim for cancer?	\	Claim-(Disease, Amount)
Can I get insured with diabetes?	Disease related insure: feasibility	Insure-(Disease)-Feasibility
How long is the waiting period after get insured for depression?	Disease related insure: waiting period	Insure-(Disease, Waiting Period)
I was refused to get insured by life insurance with diabetes.	\	Operation Failed-(Disease, Insurance)
How to do insurance notice for heart attach when getting insured?	\	Insure-(Disease, notification)-Method
How much should I pay to get insured with hypertension?	\	Insure-(Disease)-How Much
I did not have depression history.	\	Deny-(Disease)
What type of insurance can guarantee toothache?	What diseases can be guaranteed	Guarantee-(Disease)-Type Consultant
How to surrender with diabetes?	\	Surrender-(Disease)- Method Consultan
Can I renew with heart disease?	\	Renewal-(Disease)-Feasibility
How can I report headache to you?	\	Report-(Disease)- Method Consultant
Is depression exempt from it?	\	Exempt-(Disease)-Type Consultant
By what means can I check diagnosis history?	\	Check-(Diagnosis)-Method Consultant
I have hypertension, can you recommend an insurance product to me?	Recommend insurance given disease	\

Figure 11: Results of manual induction and automatic induction by RCAP on the "Health" domain.

		Argumei	ıt			Problem	
Ī	账号	节假日		费用	支付失败	无法联系	上传失败
ļ	Account	Holiday		Fee	Payment failure	Contact failure	Upload Failure
	扣费账号	春节期间		运费	支付不了	打不通	上传不上
	Deduction accou	int Spring hol	iday	freight	Can't pay	Can't get through	Can't upload
	扣费账户 Payment accour	国庆 nt National I	Day	电话费 Telephone fee	无法支付 Unable to pay	接不通 unreachable	上传失败 Upload failed
	收款账户	(户 假期		服务费	支付失败	没接诵	没有上传
	Receiving account holiday		,	Service fee	Payment failed	Not connected	No upload
	,			滞纳金	1	没有人接	无法上传
	缴费账号 Checking accoun	元旦 nt New year's		Late fee	显示支付失败 Show payment failed	次有人接 No one picks up	元法上版 Unable to upload
	还款账号	休息日		邮费	付款失败	没人接听	上传不了
	Repayment accou	int Off day	7	postage	Payment fail	No one answered	Cannot upload
	现金账号	双休日		印花税	付不了款	无法连接	上传不成功
	Cash account	weekend	is	Stamp duty	Can't pay	Unable to connect	Unsuccessful upload
	保单缴费账号 Policy paymen account		and	培训费 Training fee	支付不成功 Unsuccessful Payment	联系不上 Could not be reached	不能上传了 Can't upload anymore
	Action						
		Action				Question	
	填写 Fill In	Action 更换 Change	Del	延迟交费 aved Payment	为什么 Why	Question 怎么做 How	哪里 Where
	Fill In	更换 Change	Del	ayed Payment	Why	怎么做 How	Where
		更换 Change 改换		ayed Payment 推迟缴费	Why 为什么	怎么做 How 怎么办	
	Fill In 选 selected	更换 Change		ayed Payment	Why 为什么 Why is	怎么做 How 怎么办 In what way	Where 哪儿 Where is
	Fill In 选 selected 填	更换 Change 改换		ayed Payment 推迟缴费	Why 为什么 Why is 为啥	怎么做 How 怎么办 In what way 要怎样	Where 哪儿 Where is 哪儿呢
	Fill In 选 selected	更换 Change 改换 changed	De	ayed Payment 推迟缴费 ferred payment	Why 为什么 Why is	怎么做 How 怎么办 In what way	Where 哪儿 Where is
•	Fill In 选 selected 填	更换 Change 改换 changed 换一个	De	ayed Payment 推迟缴费 ferred payment 延迟交费	Why 为什么 Why is 为啥	怎么做 How 怎么办 In what way 要怎样	Where 哪儿 Where is 哪儿呢
	连 selected 填 fill 填写 Fill in	更换 Change 改换 changed 换一个 Change another 换下 replace	De	ayed Payment 推迟缴费 ferred payment 延迟交费 layed payment 延迟缴费 .ate payment	Why 为什么 Why is 为啥 Why do 为什么呢 For what cause	怎么做 How 怎么办 In what way 要怎样 How to 怎样 In what manner	Where 哪儿 Where is 哪儿呢 Where do 在哪里
	序訓 In 选 selected 填 fill 填写 Fill in	更换 Change 改换 changed 换一个 Change another 换下 replace 改下	De	ayed Payment 推迟缴费 ferred payment 延迟交费 layed payment 延迟缴费 .ate payment 晚点交	Why 为什么 为什么 Why is 为哈 Why do 为什么呢 For what cause 为什么会	怎么做 How 怎么办 In what way 要怎样 How to	Where 哪儿 Where is 哪儿呢 Where do 在哪里 At what place 去哪里
	Fill In 选 selected 填 fill 填写 Fill in 输入 input	更换 Change 改换 changed 换一个 Change another 换下 replace 改下 change	De	推迟缴费 ferred payment 延迟交费 layed payment 延迟缴费 ate payment 晚点交 Late pay	Why 为什么 Why is 为啥 Why do 为什么呢 For what cause 为什么会 Why	怎么做 How 怎么办 In what way 要怎样 How to 怎样 In what manner 咋么弄 How to do	Where 哪儿 Where is 哪儿呢 Where do 在哪里 At what place 去哪里 At which place
	连 selected 填 fill 填写 Fill in 输入 input 录入	更换 Change 改换 changed 换一个 Change another 换下 replace 改下 change 改一下	De De	ayed Payment 推迟缴费 ferred payment 延迟交费 layed payment 延迟缴费 .ate payment 晚点交 Late pay 推迟交	Why 为什么 Why is 为暗 Why do 为什么呢 For what cause 为什么会 Why	怎么做 How 怎么办 In what way 要怎样 How to 怎样 In what manner 咋么弄 How to do	Where 哪儿 Where is 哪儿呢 Where do 在哪里 At what place 去哪里 At which place
	连 selected 填 fill 填写 Fill in 输入 input 录入 entry	更换 Change 改换 changed 换一个 Change another 换下 replace 改下 change 改一下 Change it	De De	ayed Payment 推迟缴费 ferred payment 延迟交费 layed payment 延迟缴费 ate payment 晚点交 Late pay 推迟交 Delayed pay	Why 为什么 Why is 为啥 Why do 为什么呢 For what cause 为什么会 Why	怎么做 How 怎么办 In what way 要怎样 How to 怎样 In what manner 咋么弄 How to do	Where 哪儿 Where is 哪儿呢 Where do 在哪里 At what place 去哪里 At which place
	连 selected 填 fill 填写 Fill in 输入 input 录入	更换 Change 改换 changed 换一个 Change another 换下 replace 改下 change 改一下	De De	ayed Payment 推迟缴费 ferred payment 延迟交费 layed payment 延迟缴费 .ate payment 晚点交 Late pay 推迟交	Why 为什么 Why is 为暗 Why do 为什么呢 For what cause 为什么会 Why	怎么做 How 怎么办 In what way 要怎样 How to 怎样 In what manner 咋么弄 How to do	Where 哪儿 Where is 哪儿呢 Where do 在哪里 At what place 去哪里 At which place
	度 定 定 定 定 定 に に は 頂 所 間 に 編 所 に に に に に に に に に に に に に	更换 Change	De De	ayed Payment 推迟缴费 ferred payment 延迟效费 layed payment 延迟缴费 .ate payment 晚点交 Late pay 推迟交 Delayed pay 迟交	Why 为什么 Why is 为啥 Why do 为什么呢 For what cause 为什么会 Why 为什么会这样 What's the cause 什么原因	怎么做 How 怎么办 In what way 要怎样 How to 怎样 in what manner 咋么弄 How to do 怎么弄 By what method	Where 哪儿 哪儿吧 Where is 哪儿呢 Where do 在哪里 At what place 去哪里 At which place 到哪里 What is the place 哪咤 To where
	Fill In 选 selected 填 fill 填 写 Fill in 输加 和 和 和 和 和 和 和 和 和	更换 Change 改换 changed 块e—h Change another 块下 replace 改下 change 改一下 Change it 修改	De De	ayed Payment 推迟缴费 ferred payment 延迟交费 layed payment 延迟缴费 .ate payment 晚点交 Late pay 推迟交 belayed pay 迟交	Why 为什么 Why is 为啥 Why do 为什么呢 For what cause 为什么会 Why 为什么会这样 What's the cause	怎么做 How 怎么办 In what way 要怎样 How to E In what manner 咋么弄 How to do 怎么弄 By what means	Where 哪儿 Where is 哪儿呢 Where do 在哪里 At what place 去哪里 At which place 到哪里 What is the place 哪呢

Figure 9: Typical concepts for all four intent-roles: Argument, Problem, Action, and Question.

A.5 Schema Induction Results

We enumerate the induced intents in Sec. 5.3 by the manual procedure and our RCAP and show them in Fig. 11.

A.6 Concepts Expansion

Though concepts are mined from a large-scale open-domain corpus, they may be still missed in new domains. To enrich the concepts and enhance the feasibility of RCAP induced schemas in new domains, we will conduct concept expansion on new utterances when they come from new domains.

Here, we first extract the corresponding intent-role mentions from the utterances. After that, we assign these mentions to existing concepts by directly matching. If they are not matched, we conduct concept inference on them. Hence, there exist some mentions that cannot be inferred to a certain concept with high confidence since they may not have enough qualified neighbors; see details in ConInfer function of Algo. 1. Here, we tune δ and K to control the confidence level for concepts expansion. We then collect these uncategorized mentions and feed them to concept mining process to find new concepts. Due to the simple structure of RCAP, new concepts are incremental to the original concept schema.

A.7 Dataset Release

We release a sample set with 324 utterances from ECD. All other datasets are under review and the desensitized datasets will be released after publication.