

DiaKG: an Annotated Diabetes Dataset for Medical Knowledge Graph Construction

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Abstract. Knowledge Graph has been proven effective in modeling structured information and conceptual knowledge, especially in the medical domain. However, the lack of high-quality annotated corpora remains a crucial problem for advancing the research and applications on this task. In order to accelerate the research for domain-specific knowledge graphs in the medical domain, we introduce DiaKG, a high-quality Chinese dataset for Diabetes knowledge graph, which contains 22,050 entities and 6,890 relations in total. We implement recent typical methods for Named Entity Recognition and Relation Extraction as a benchmark to evaluate the proposed dataset thoroughly. Empirical results show that the DiaKG is challenging for most existing methods and further analysis is conducted to discuss future research direction for improvements. We hope the release of this dataset can assist the construction of diabetes knowledge graphs and facilitate AI-based applications.

Keywords: Diabetes · Dataset · Knowledge graph.

1 Introduction

Diabetes is a chronic metabolic disease characterized by high blood glucose level. Untreated or uncontrolled diabetes can cause a range of complications, including acute ones like diabetic ketoacidosis and chronic ones such as cardiovascular diseases and diabetic nephropathy. With the rapid economic developments and changes in lifestyle, China has become the country with the most diabetes patients in the world: the prevalence of diabetes in Chinese adults is about 11.2% and still increasing[1]. The medical expenses from diabetes without complications already account for 8.5% of national health expenditure in China[2]. Cardiovascular diseases, one of the complications of diabetes, are the leading cause of death in China. Diabetic nephropathy, another diabetes complication, could “waste the wealth that we’ve accumulated over the past 30 years in the drains of dialysis machines” according to [3]. As a result, diabetes is a serious public health problem in the realization of “Healthy China 2030” that requires interdisciplinary innovations to solve.

Knowledge Graph (KG) has been proven effective in modeling structured information and conceptual knowledge, especially in the medical domain[4]. Medical knowledge graph is attracting attention from both academic and healthcare industries due to its power in intelligent healthcare applications, such as clinical decision support systems (CDSSs) for diagnosis and treatment[5,6], self-diagnosis utilities to assist patient evaluating health conditions based on symptoms[7,8]. High-quality entity and relation corpus is crucial for constructing knowledge base, however, there is no dataset dedicated to the diabetes disease at the moment. To address this issue, we introduce DiaKG, a high-quality Chinese dataset for Diabetes knowledge graph construction.

The contributions of this work are as follows:

1. To the best of our knowledge, this is the first diabetes dataset for medical knowledge graph construction at home and abroad.

2. In addition to the medical experts, we also introduce AI experts to participate in the annotation process to provide data insight, which improves the usability of DiaKG and finally benefits the end-to-end model performance.

We hope the release of this corpus can help researchers develop knowledge bases for clinical diagnosis, drug recommendation, and auxiliary diagnostics to further explore the mysteries of diabetes. The datasets are publicly available at <https://tianchi.aliyun.com/dataset/dataDetail?dataId=88836>

2 DiaKG Construction

2.1 Data Resource

The dataset is derived from 41 diabetes guidelines and consensus, which are from authoritative Chinese journals covering the most extensive fields of research content and hotspot in recent years, including clinical research, drug usage, clinical cases, diagnosis and treatment methods, etc. Hence it is a quality-assured resource for constructing a diabetes knowledge base.

2.2 Annotation Guide

Two seasoned endocrinologists designed the annotation guide. The guide focuses on entities and relations since these two types are the fundamental elements of a knowledge graph.

Entity 18 types of entities are defined(Table.1). Nested entities are allowed; for example, '2型糖尿病' is a 'Disease' entity, and '2型' is a 'Class' one. Entities in DiaKG has two characteristics that stand out: 1. Entities may attribute to different types according to the contextual content; for example, '糖尿病' in sentence '糖尿病患者需控制饮食' is a 'Disease' type, while in the sentence '糖尿病所致肾损伤占1/3' serves as a 'Reason' type; 2. Some entity types are of long spans, like 'Pathogenesis' type is usually consisted of a sentence.

Table 1. List of entities

entity name	example	# num	avg length
疾病(Disease)	运动对1型糖尿病微血管病变的预后无改善作用	5,743	7.3
疾病分期分型(Class)	心功能III-IV级、终末期肾病	1,262	4.3
病因(Reason)	若体重增加,可能加重胰岛素抵抗	175	7.3
发病机制(Pathogenesis)	多数患者的β细胞完全破坏	202	10.3
临床表现(Symptom)	已发生明确的足趾、足掌坏疽创面	479	5.8
检查方法(Test)	进行混合餐耐量试验(MMTT)	489	6.1
检查指标(Test_Items)	测量指血(毛细血管血)血糖	2,718	7.7
检查指标值(Test_Value)	血糖<3.3mmol/L	1,356	9.5
药物名称(Drug)	包括COX-2抑制剂	4,782	7.8
用药频率(Frequency)	按照0.5mg, 1~3次/d	156	4.7
用药剂量(Amount)	可根据0.3~0.5单位/千克体重来估算	301	6.7
用药方法(Method)	短效胰岛素一般在餐前15~30min皮下注射	399	6.1
非药物治疗(Treatment)	认知-行为及心理干预是调整患者的生活环境	756	8.0
手术(Operation)	进行胰岛细胞移植手术来改善胰岛情况	133	9.0
不良反应(ADE)	贝特类可使胆结石的发生率升高	874	5.1
部位(Anatomy)	微血管和大血管并发症等方面的证据	1,876	3.1
程度(Level)	对于中到重度肾功能不全患者需减少剂量	280	2.9
持续时间(Duration)	预防治疗维持3~6个月	69	3.7

Relation Relations are centered on 'Disease' and 'Drug' types, where a total of 15 relations are defined(Table.2). Relations are annotated on the paragraph level, so entities from different sentences may form a relation, which has raised the difficulty for the relation extraction task. Head entity and tail entity existing in the same sentence only account for 43.4% in DiaKG.

2.3 The Annotation Process

The annotated process is shown in Fig.1. The process can be divided into two steps:

OCR Process The PDF files are transformed to plain text format via the OCR tool¹, where non-text data like figures and tables are manually removed. Additionally 2 annotators manually check the OCR results character by character to avoid misrecognitions, for example, 'β细胞' may be recognized as 'B细胞'.

Annotation Process 6 M.D. candidates were employed and were trained thoroughly by our medical experts to have a comprehensive understanding of the annotation task. During the **trial annotation** step, we creatively invited 2 AI experts to label the data simultaneously, based on the assumption that AI experts could provide data insight from the model's perspective. For example, medical experts are inclined to label '成年型糖尿病(maturity-onset diabetes of the young, MODY)' as a whole entity, while AI experts regard '成年型糖尿

¹ <https://duguang.aliyun.com/>

Table 2. List of relations

relation	example	# num
TestItems_Disease	血浆酮体增加或酮血症倾向低于正常人	1,171
Treatment_Disease	积极进行糖尿病防治知识的宣教, 增加运动	354
Class_Disease	分级I-II级的充血性心力衰竭的患者	854
Anatomy_Disease	慢性并发症如各种神经病变、视网膜病变等	195
Drug_Disease	二甲双胍可有效改善糖尿病的IR	1,315
Reason_Disease	慢性梗阻可引起肾积水和肾实质萎缩	164
Symptom_Disease	对糖尿病足溃疡及...更好地体现了创面感染的情况	283
Operation_Disease	接受糖尿病外科手术患者...对接受减重代谢手术的病人	37
Test_Disease	5项检查(...温度觉)等方法半定量评估患者的神经病变程度	271
Pathogenesis_Disease	二甲双胍可改善IR...更全面针对T2DM的生理缺陷的特点	130
ADE_Drug	正确使用磺脲类药物..., 轻、中度低血糖发生率为...	693
Amount_Drug	二甲双胍(1000mg/d)起始治疗	195
Method_Drug	短效胰岛素一般在餐前15~30min皮下注射	185
Frequency_Drug	每日1次基础胰岛素或...作为胰岛素起始治疗方案	103
Duration_Drug	持续静脉泵注胰岛素有利于减少血糖波动	61

病’, ‘maturity-onset diabetes of the young’ and ‘MODY’ as three separate entities are more model-friendly. Feedback from AI experts and the annotators were sent back to the medical expert to refine the annotation guideline iteratively. The **formal annotation** step started by the 6 M.D. candidates and 1 medical experts would give timely help when needed. **The Quality Control (QC)** step was conducted by the medical experts to guarantee the data quality, and common annotation problems were corrected in a batch mode. The final quality is evaluated by the other medical expert via random sampling of 300 records. The accuracy rates of entity and relation are 90.4% and 96.5%, respectively, demonstrating the high-quality of DiaKG. The examined dataset contains 22,050 entities and 6,890 relations, which is empirically adequate for a specified disease.

2.4 Data Statistic

Detailed statistical information for DiaKG is shown in Table.1 and Table.2.

3 Experiments

We conduct Named Entity Recognition(NER) and Relation Extraction(RE) experiments to evaluate DiaKG. The codebase is public on github¹, and the implementation details are also illustrated on the github repository.

3.1 Named Entity Recognition (NER)

We only report results from X Li et al.(2019)[10] since it is the SOTA model for NER with nested settings at the time of this writing.

¹ <https://github.com/changdejie/diaKG-code>

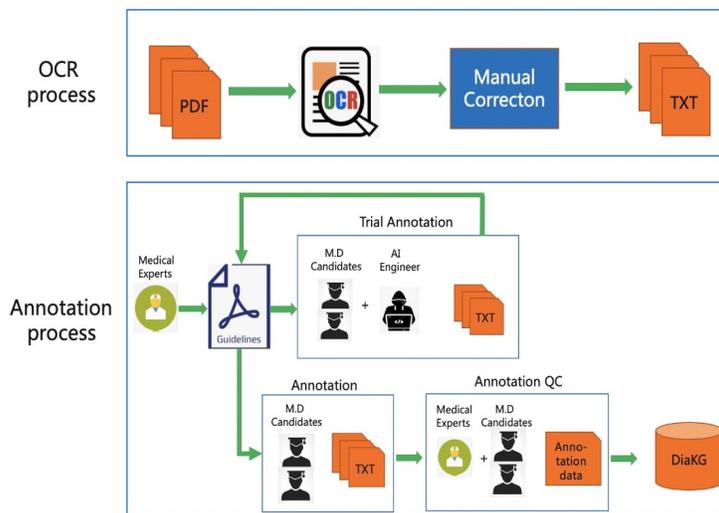


Fig. 1. The annotated process of the diabetes dataset.

3.2 Relation Extraction (RE)

The RE task is defined as giving the head entity and the tail entity, to classify the relation type. Many sophisticated methods[9] for RE have been proposed recently, due to the simplified setting, we report results from bi-directional GRU-attention[11] in this paper.

Table 3. selected NER results				Table 4. selected RE results			
Entity	precision	recall	F1	Relation	precision	recall	F1
total	0.814	0.853	0.833	total	0.839	0.837	0.836
Drug	0.881	0.902	0.892	Class_Disease	0.968	0.874	0.918
Disease	0.794	0.91	0.848	ADE_Drug	0.892	0.892	0.892
Pathogenesis	0.595	0.667	0.629	Test_Disease	0.648	0.636	0.642
Symptom	0.535	0.535	0.535	Pathogenesis_Disease	0.486	0.692	0.571
Reason	0.333	0.3	0.316	Operation_Disease	0.6	0.231	0.333

4 Analysis

The experimental results are shown in Table.3 and Table.4. We report the total result, plus the top 2 and last 3 types' results for each task to analyze DiaKG.

The **overall** macro-average scores for the two tasks are 83.3% and 83.6%, respectively, which are satisfying considering the multifarious types we define, also demonstrating DiaKG's high quality. For the **NER task**, the results of 'Disease' and 'Drug' types are as expected because these two types exist frequently among the documents, thus leading to a higher score. The average entity length for 'Pathogenesis' type is 10.3, showing that the SOTA MRC-Bert model still can not handle the long spans perfectly; We analyzed errors of the 'Symptom'

and 'Reason' types and found that the model is prone to classify entities as other types, mainly contributing to the characteristic that entity may be of different types due to the contextual content. For the **RE task**, the case study shows that entities with long distance are difficult to classify. For example, entities with 'Drug_Disease' type usually exist in the same sub-sentence, whereas the ones with 'Reason_Disease' type are usually located in different sub-sentences, sometimes even in different sentences. The above experimental results demonstrate that DiaKG is challenging for most current models and it is encouraged to employ more powerful models on this dataset.

5 Conclusion & Future Work

In this paper, we introduce DiaKG, a specified dataset dedicated to the diabetes disease. Through a carefully designed annotation process, we have obtained a high-quality dataset. The experiment results prove the practicability of DiaKG as well as the challenges for the most recent typical methods. We hope the release of this dataset can advance the construction of diabetes knowledge graphs and facilitate AI-based applications. We will further explore the potentials of DiaKG and contribute it to the CBLUE[12] community.

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