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I型糖尿病血管病变的预测无改善作用                             | 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、足掌疼痛创面                                         | 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) | 测量空腹(毛细血管)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/天                                                  | 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        |
| 非药治疗(Treatment) | 认知-行为及心理干预等调整患者的生活环境                              | 756   | 8.0        |
| 手术(Operation)     | 肾岛细胞移植手术来改善胰岛情况                                       | 133   | 9.0        |
| 不良反应(ADE)      | 与特美可使肌钙蛋白的发生率升高                                       | 874   | 5.1        |
| 部位(Anatomy)       | 微血管和大血管并发病等的证据                                        | 1,876 | 3.1        |
| 病理(Reason)        | 乙肝患者肝功能不全患者可能减少剂量                                   | 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                                  | 1171  |
| Treatment_Disease    | 积极进行糖尿病防治知识的宣传，增加运动                                 | 354   |
| Class_Disease        | 分级I-II级的无心脏病史的患者                                           | 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                                         | 1315  |
| 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者...对接受减重代谢手术的病人                       | 37    |
| Test_Disease         | 5项检查(...温度宽)等方法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...的生理缺陷的特点                            | 130   |
| ADE_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次注射胰岛素或...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    |

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 github\(^1\), 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
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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