Construction and Applications of Open Business Knowledge Graph

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Abstract

Business Knowledge Graph is important to many enterprises today, providing the factual knowledge and structured data that steer many products and make them more intelligent. Despite the welcome outcome, building business KG brings prohibitive issues of deficient structure, multiple modalities and unmanageable quality. In this paper, we advance the practical challenges related to building KG in non-trivial real-world systems. We introduce the process of building an open business knowledge graph (OpenBG) derived from a well-known enterprise. Specifically, we define a core ontology to cover various abstract products and consumption demands, with fine-grained taxonomy and multi-modal facts in deployed applications. OpenBG is ongoing, and the current version contains more than 2.6 billion triples with more than 88 million entities and 2,681 types of relations. We release all the open resources (OpenBG benchmark) derived from it for the community. We also report benchmark results with best learned lessons†.

1 Introduction

Knowledge Graphs (KGs) have attracted widespread attention from both academia and industry over the years (Noy et al., 2019; Mondal et al., 2021), and have been widely applied in many fields, such as education (Chen et al., 2018; Shen et al., 2021), biomedical science (Li et al., 2020; Liu et al., 2021; Zhang et al., 2022), finance (Ding et al., 2016; Deng et al., 2019). Recently, business has penetrated almost all areas of social life, and business KG (Xu et al., 2020; Zhang et al., 2021) has been accumulating a large amount of data in different fields consequently (Qiu et al., 2015; Embar et al., 2020; Yan et al., 2021). Although flourishing business KG has shown tremendous potentials in many applications, it still faces enormous challenges.

![Figure 1: Challenges of building large-scale business KG from multi-source and noisy big data.](image)

**Challenges.** (1) **deficient structure.** Due to the noise and redundancy inevitably exist in big data, large-scale business KGs built with it often suffer from structural defects. For example, as seen in Figure 1, “China” is both an instance of a class (Place) and a value of an attribute (placeOfOrigin), showing redundancy in definition; “Cooking” and “Make Sushi” have an upper-lower relationship but are disconnected in KG, showing unhealth in KG schema. (2) **multiple modalities.** As the big data are derived from multimedia sources, thus they can be formatted in multiple modalities, e.g., texts, images, and tables, making it challenging to build such a multi-modal KG from multi-source data. For example in Figure 1, to present a product “iPhone 13 Pro”, titles, technical specifications, advertising slogans, and product images are all required to format in a universal way. (3) **unmanageable quality.** Quality management is vital for business KGs, as KG quality has not been high enough yet, which severely restricts downstream applications. In Figure 1, we list some dimensions of KG quality referring to Wang et al. (2021c), which are really difficult to manage and evaluate in non-trivial real-world business scenarios.
To tackle the challenges and address the technological limitations, we introduce the process of building an open business knowledge graph (OpenBG) which is deployed for real-world use, and release open resources (OpenBG benchmarks) derived from it. Specifically, we build OpenBG from big open data by designing a core ontology, mainly containing 8 types of core classes/concepts and 2,681 types of relations. We then enrich OpenBG with large-scale multi-modal product triples and polish the original ontology with triple accumulation. Finally we release the ongoing OpenBG containing 1,131,579 core classes/concepts, 88,881,723 entities, and 2,603,046,837 triples. To simplify the usage, we also release OpenBG benchmarks, sampled from OpenBG, for research analysis and industrial applications. Besides, we run an online competition based on OpenBG, which has attracted thousands of participants.

Contributions of this work can be summarized:

- We introduce the practical issues and technical solutions related to the open business knowledge graph construction in non-trivial real-world systems.
- We publish OpenBG, an ongoing business KG from multi-modal and noisy big data, containing more than 88 million entities and 2.6 billion triples.
- We define metrics to evaluate the quality of KG, and release OpenBG benchmarks for simplified utility, which can hopefully enlighten KG construction in other fields.

2 Open Business Knowledge Graph

2.1 Preliminary

Defining the ontology (or schema) is fundamental for KG construction, which imposes constraints on the links coupled with business logic. We present the core ontology of OpenBG in Figure 2, with references to W3C standards, mainly containing classes/concepts and relations.

Core Classes/Concepts: We have defined 3 types of core classes to express knowledge related to products (i.e., “Category”, “Place”, “Brand”) and 5 types of core concepts to express knowledge related to business concepts (i.e., “Time”, “Scene”, “Market Segment”, “Crowd” and “Theme”), where Category indicates the taxonomy of products and is the central node in OpenBG ontology. Note that classes with rich semantics often have various properties, and concepts defined by Simple Knowledge Organization System (SKOS) are deemed as simple classes because they are abstract entities without complex semantics, similarly defined with AliCoCo (Luo et al., 2020).

Core Relations: (1) We have defined 2,310 types of object properties to model associative relationships among core classes/concepts, such as brandIS, placeOfOrigin, appliedTime, relatedScene, aboutTheme, forCrowd, inMarket* (a relation set including 2,304 subproperties). (2) Besides, we have imported another 4 types of meta-properties defined by W3C standards to express taxonomy, synonymy and instantiation of classes/concepts, i.e., rdfs:subClassOf, skos:broader, owl:equivalentClass, and rdf:type. (3) Moreover, we also have imported 2 types of meta-properties to express property of properties, i.e., rdfs:subPropertyOf and owl:equivalentPropertyOf.

2.2 Construction of Ontology Classes

In this section, we present the construction of 3 core classes, i.e., “Category”, “Place”, “Brand”.

Construction of “Category”. We follow a top-down approach to constructing Category.

(1) Define “Category” and taxonomy. We first...
create a single top-level class: Category, before specializing it with subclasses. We further break down each class layer by layer, for example, *electronic components* are broken down into some subclasses, such as *LED, power supply*, etc. To evaluate the quality of Category definition, we propose a metric named *Health Degree of Category* (HDC).

**Definition 2.1. Health Degree of Category (HDC).** A metric to measure the degree of healthy definition for a category, w.r.t. some indices including cleanliness $C$, completeness $M$, exclusiveness $X$, effectiveness $F$ and recognition $G$.

Specifically, the five indices reflect HDC from different perspectives.

(i) $C$ denotes the cleanliness and reasonableness of a label definition.

(ii) $M$ denotes the completeness of a category containing child nodes.

(iii) $X$ presents if a category excludes child nodes of other categories.

(iv) $F$ indicates the popularity of products associated with a category.

(v) $G$ reflects the recognition of a category from customers and sellers.

Then we can calculate $HDC$ by

$$HDC = C + M + X + F + G$$  \hspace{1cm} (1)

where $C, M, X, F, G \in [0, 10]$ and are measured by experts on business. If a category is more qualified for these five indices, it will obtain a higher score of $HDC$, meaning that the category definition is more healthy.

(2) **Create multi-modal instances of “Category”**. In fact, the instances of “Category” are products in business. We randomly sample some products for each leaf node in category taxonomy from an e-commerce platform. We define object properties to support products associated with other classes/concept, e.g., (iPhone 13 Pro, brand1s, Apple). We then define data properties of each product to express its attribute-related information, e.g., (iPhone 13 Pro, Size, 6.1 inches). Particularly, we select the textual corpus of product description and images of products from an e-commerce platform, making products in OpenBG becoming multi-modal with textual descriptions and images.

**Construction of “Place” and “Brand”.** We generally utilize a schema mapping approach (Shen et al., 2021; Chen et al., 2017) to construct “Place” and “Brand” from diverse sources.

(1) **Define “Place” and taxonomy.** We integrate and transform administrative region data in different formats from diverse KGs, such as Wikidata6, OpenKG7. The taxonomy of “Place” includes country or great region, province, city, county, village/town in order.

(2) **Define “Brand” and taxonomy.** “Brand” is divided into 45 major categories following the guideline for declaration of goods8, e.g., Clothes, Furniture, and Vehicle. We also integrate and transform various kinds of brand-related data from authoritative websites, e.g., the profile of a brand on its official homepage.

(3) **Link “Place” and “Brand” with products.** We link “Place” and “Brand” to products via labels. For each product containing place and brand information, we map the labels of its place and brand to standard names defined in “Place” and “Brand” taxonomy, with jointly conducting trie prefix tree precise matching and fuzzy matching of synonyms.

2.3 **Construction of Ontology Concepts**

OpenBG currently contains 5 types of core concepts, i.e., Scene, Crowd, Theme, Time, and Market Segment. We follow a bottom-up approach for Concept taxonomy construction.

(1) **Create instances of “Concept”**. We first leverage sequence labeling to extract concepts from real-world large-scale business text corpus, such as user-written reviews, product titles, and search queries. We utilize BERT-CRF model, a popular model for many sequence labeling tasks (Zhang et al., 2020; Pang et al., 2019). BERT-CRF model consists of a BERT layer and a CRF (Conditional Random Field) layer, where BERT (Devlin et al., 2019) enables to get a contextual representation for each word and CRF considers the correlations between the current label and neighboring labels.

(2) **Define “Concept” and taxonomy.** Given the 5 top-level broad concepts: Scene, Crowd, Theme, Time, and Market Segment, we classify instances of “Concept” into the 5 ones. Then we summarize the narrower concepts to broader ones level by level, until to the top level. Specifically, to evaluate the quality of concepts, we organize concepts lie in different perspectives.

(i) **Plausibility**: Indicating whether a statement is meaningful, e.g., ⟨sports shoes, forCrowd, the...
elderly), where sports shoes are products and the elderly are a narrower concept of Crowd.

(ii) Typicality: Indicating whether a statement is valid for most instances, e.g., (lightweight sports shoes, for Crowd, the elderly) are typical while (trendy sports shoes, for Crowd, the elderly) are not, because trendy shoes are not suitable for most elderly people.

(iii) Remarkability: Indicating whether a concept is distinguishable enough from closely related ones, e.g., (non-slip shoes, for Crowd, the elderly) are remarkable while (thin and light shoes, for Crowd, the elderly) are not, because thin and light shoes are also suitable for young people.

(iv) Salience: Indicating whether a concept is representative and knowledge enough, so that instances can be associated with it spontaneously. Generally, a statement both satisfying Typicality and Remarkability implies Salience.

2.4 Applications

OpenBG can be applied to numerous real-world applications in business scenarios, including in this paper but not limited to:

(1) Prompt Product Release. The target is to release emerging products. With OpenBG, when emerging products release, their attribute information can be automatically filled in, so as to improve efficiency and decrease duration. The evaluation metric is Duration of emerging products release.

(2) Item Alignment. The target is to identify different items referring to the same product. With OpenBG, items referring to the same product can be recognized more easily based on the product schema. The evaluation metric is Gross Merchandise Volume (GMV) of aligned items.

(3) Shopping Guide. The target is to guide users to purchase items. With OpenBG, items can be tagged with various concepts and linked with more enriched information, so that users can better understand items and intend to consume. The evaluation metric is Cost Per Mille (CPM).

(4) QA-based Product Recommendation. The target is to recommend items to users in QA scenarios. With OpenBG, AliMe (a smart QA robot) (Li et al., 2017) can better understand users’ intention and recommend items more precisely. The evaluation metric is Click-Through-Rate (CTR).

We show the proportion of performance improvement after deploying OpenBG in the downstream tasks, referred to Table 1.

Table 1: Evaluation results of business application with deployment of OpenBG. (Duration is lower is better; GMV, CPM, CTR are all larger are better.)

| Application | Evaluation Metric | Ratio of improvement |
|-------------|-------------------|----------------------|
| Prompt Product Release | Duration | ~30%↑ |
| Item Alignment | GMV(for aligned items) | ~45%↑ |
| Shopping Guide | CPM | ~28.1%↑ |
| QA-based Recommendation | CTR | ~11%↑ |

3 Open Resources: OpenBG

To promote further research in developing plausible KG representation solutions to real-world applications, we present the OpenBG Benchmark, a challenging benchmark to facilitate reproducible, scalable, and multimodal KG research. We also conduct experiments and release leaderboards publicly available at https://tianchi.aliyun.com/dataset/dataDetail?dataId=122271&lang=en-us.

3.1 Benchmark Construction

OpenBG benchmark contains several subsets of OpenBG, including OpenBG-IMG, OpenBG500, and OpenBG500-L. Thereinto, OpenBG-IMG is a small multi-modal dataset, OpenBG500 is a unimodal dataset, while OpenBG500-L is a large-scale version of OpenBG500, aiming to benchmark efficient machine learning methods over the large-scale KG. We show the statistical details of OpenBG benchmarks and comparison with WikidataSM (Wang et al., 2021d) and OGB (Hu et al., 2020, 2021) in Table 2. Besides, we also present the statistic and cases of OpenBG (full) in Appendix A.1 and A.2.

Table 2: Summary statistics of OpenBG datasets. ↑: there are 14,718 multi-modal entities in OpenBG-IMG. OpenBG (Full) do not have a train/dev/test split. OGB-LSC refers to the WikiKG900Mv2 in OGB-LSC.

| Dataset      | # Ent | # Rel | # Train | # Dev | # Test |
|--------------|-------|-------|---------|-------|--------|
| OpenBG-IMG   | 27,910 | 2,681  | 220,087 | 5,000 | 14,675 |
| OpenBG500    | 2,782,223 | 47,410,032 | 1,242,550 | 5,000 | 5,000 |
| OpenBG500-L  | 88,881,723 | 2,681  | 260,304,683 | 10,000 | 10,000 |
| WikidataSM   | 4,594,485 | 822    | 20,614,279 | 5,163 | 5,133  |
| OGB-LSC      | 91,230,610 | 1,387  | 608,062,811 | 15,000 | 10,000 |

Given OpenBG (full) with a full set of entities, relations, triples, denoted by \( \{ E, R, T \} \), we utilize a three-stage method to build high-quality OpenBG benchmarks, including step 1: selecting relations from \( R \) (relation refinement); step 2: filtering head entities from \( E \) (head entity filtering); step 3: sampling tail entities in triples \( T \) (tail entity sampling). Detailed processes are illustrated in Appendix A.3 due to page limits.
(1) Relation Refinement. We follow two principles to manually filter representative relations in OpenBG: (i) To select high-frequency relations, as they are supposed to imply a relatively high-value applications. (ii) To select closely business-related relations, as they directly describe the attributes of products. In this way, we obtain relation subsets $R^{500}, R^{500-L}$ and $R^{136}$, respectively containing 500 (for OpenBG500 & OpenBG500-L) and 136\(^9\) (for OpenBG-IMG) relations, where $R^{136} \subset R^{500}, R^{500-L} \subset R$. We show the distribution of 136 relations in OpenBG-IMG, as seen in Figure 3, which is in long-tail scenarios. OpenBG500 and OpenBG500-L also follow similar relation distributions shown in Appendix A.4.

(2) Head Entity Filtering. Regarding the long-tail relation distribution of $R^{136}, R^{500},$ and $R^{500-L}$, we split $R^N$ ($N = 136, 500, 500-L$) into head-relation $R^N_{\text{head}}$ and tail-relation $R^N_{\text{tail}}$. Then we divide the entities into $R^N_{\text{head}}$ tail relations $R^N_{\text{tail}}$ entities $(E_{R^N_{\text{head}}})$ and $R^N_{\text{tail}}$ entities $(E_{R^N_{\text{tail}}})$, and distribute sampling rate $\alpha^h_N$ for the former, and $\alpha^t_N$ for the latter, where $\alpha^h_N > \alpha^t_N$. The entity sampling can be denoted by:

$$E^N = \text{Sample}(E_{R^N_{\text{head}}}, \alpha^h_N) + \text{Sample}(E_{R^N_{\text{tail}}}, \alpha^t_N)$$

where \(\text{Sample(Set, Rate)}\) denotes randomly sampling the Set at a certain Rate, and $E^N$ ($N = 136, 500, 500-L$) is the sampled entities.

(3) Tail Entity Sampling. Given the filtered relations $R^N$ ($N = 136, 500, 500-L$) and sampled head entities $E^N$ in triples, We firstly filter triples $\mathcal{T}(E^N, R^N)$ from $\mathcal{T}$ by connecting $E^N$, $R^N$ and all tail entities of $R^N$, and then build three benchmarks $\mathcal{T}^N$ ($N = 136, 500, 500-L$) entitiled OpenBG-IMG, OpenBG500, OpenBG500-L through sampling tail entities from $\mathcal{T}(E^N, R^N)$ and connecting them with head entities $E^N$ and relations $R^N$ to obtain the whole triples, denoted by:

$$\mathcal{T}^N = \text{Sample}(\mathcal{T}(E^N, R^N), \alpha^N)$$

where $\alpha^N$ is determined by each benchmark $\mathcal{T}^N$.

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Table 3: Results of the link prediction on OpenBG-IMG. The bold numbers denote the best results.

| Model                  | Hits@1↑ | Hits@3↑ | Hits@10↑ | MR↓ | MRR↑ |
|------------------------|---------|---------|----------|-----|------|
| Unimodal approach      |         |         |          |     |      |
| TransE (Bordes et al., 2013) | 0.150   | 0.387   | 0.647    | 118 | 0.315 |
| TransH (Wang et al., 2014) | 0.129   | 0.525   | 0.743    | 112 | 0.357 |
| TransD (Ji et al., 2015) | 0.137   | 0.532   | 0.746    | 110 | 0.364 |
| DistMult (Yang et al., 2015) | 0.060   | 0.157   | 0.279    | 524 | 0.139 |
| ComplEx (Trouillon et al., 2016) | 0.143   | 0.244   | 0.371    | 782 | 0.221 |
| TuckER (Balazevic et al., 2019) | 0.497   | 0.690   | 0.820    | 1473| 0.611 |
| KG-BERT (Yao et al., 2019) | 0.092   | 0.207   | 0.405    | 61  | 0.194 |
| StAR (Wang et al., 2021a) | 0.176   | 0.307   | 0.493    | 79  | 0.280 |
| Multimodal approach    |         |         |          |     |      |
| TransAE (Wang et al., 2019) | 0.274   | 0.489   | 0.715    | 36  | 0.421 |
| RSME (Wang et al., 2021b) | 0.485   | 0.687   | 0.838    | 72  | 0.607 |
| MKGformer (Chen et al., 2022) | 0.448   | 0.651   | 0.822    | 23  | 0.575 |

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Table 4: Results on OpenBG500 and OpenBG500-L. The bold numbers denote the best results.

| Model                  | Hits@1↑ | Hits@3↑ | Hits@10↑ | MR↓ | MRR↑ |
|------------------------|---------|---------|----------|-----|------|
| OpenBG500              |         |         |          |     |      |
| TransE (Bordes et al., 2013) | 0.207   | 0.340   | 0.513    | 5381| 0.304 |
| TransH (Wang et al., 2014) | 0.143   | 0.402   | 0.569    | 6501| 0.296 |
| TransD (Ji et al., 2015) | 0.146   | 0.411   | 0.576    | 6129| 0.302 |
| DistMult (Yang et al., 2015) | 0.068   | 0.131   | 0.255    | 5799| 0.129 |
| ComplEx (Trouillon et al., 2016) | 0.081   | 0.187   | 0.313    | 6393| 0.156 |
| TuckER (Balazevic et al., 2019) | 0.428   | 0.615   | 0.735    | 2573| 0.541 |
| KG-BERT (Yao et al., 2019) | 0.071   | 0.145   | 0.262    | 401 | 0.138 |
| GenKGC (Xie et al., 2022) | 0.203   | 0.280   | 0.351    | -   | -    |
| OpenBG500-L             |         |         |          |     |      |
| TransE (Bordes et al., 2013) | 0.141   | 0.427   | 0.543    | 6501| 0.296 |
| TransH (Wang et al., 2014) | 0.146   | 0.411   | 0.576    | 6129| 0.302 |
| TransD (Ji et al., 2015) | 0.058   | 0.103   | 0.213    | 5799| 0.129 |
| DistMult (Yang et al., 2015) | 0.081   | 0.187   | 0.313    | 6393| 0.156 |
| ComplEx (Trouillon et al., 2016) | 0.081   | 0.187   | 0.313    | 6393| 0.156 |
| TuckER (Balazevic et al., 2019) | 0.428   | 0.615   | 0.735    | 2573| 0.541 |
| KG-BERT (Yao et al., 2019) | 0.071   | 0.145   | 0.262    | 401 | 0.138 |
| GenKGC (Xie et al., 2022) | 0.203   | 0.280   | 0.351    | -   | -    |

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\(^9\)Because some triples contain no image, OpenBG-IMG has fewer relations than OpenBG500.
3.2 Benchmark Settings

To evaluate the quality of OpenBG benchmarks, we implement link prediction experiments, where we predict tail entity when given head entity and relation in a triple. We use top-K hitting rate (Hits@K, K=1,3,10), Mean Rank (MR), and Mean Reciprocal Ranking (MRR) as evaluation metrics. Note that OpenBG-IMG is in multi-modal settings with both texts and images, while OpenBG500 and OpenBG500-L follow vanilla settings.

3.3 Baselines Models

We implement several baselines on the three benchmarks regarding their varying scales and settings.

1) Uni-modal KG embedding approaches for OpenBG500 & OpenBG500-L & OpenBG-IMG: TransE (Bordes et al., 2013), TransH (Wang et al., 2014), TransD (Ji et al., 2015), DistMult (Yang et al., 2015), ComplEx (Trouillon et al., 2016), TuckER (Balazevic et al., 2019), and StAR (Wang et al., 2021a) leverage the KG structure for link prediction. KG-BERT (Yao et al., 2019) utilizes the description text and pre-trained language model. Note that Since the size of OpenBG500-L is very large, we only report results on parts of baselines.

2) Multi-modal KG embedding approaches for OpenBG-IMG only: TransAE (Wang et al., 2019) uses a multi-modal auto-encoder based on TransE for a unified representation of textual and visual input. RSME (Wang et al., 2021b) designs a filter gate and a forget gate to enhance visual information learning. MKGformer (Chen et al., 2022) utilizes a hybrid transformer architecture with multi-level fusion for better multi-modal entity representation.

3.4 Overall Performance Comparison

1) Uni-modal Link Prediction. The experimental results in Table 3 and Table 4 illustrate that translational distance models (TransE, TransH, etc.) greatly outperforms normal bilinear model (DistMult, ComplEx, etc.). We notice that TuckER can archive higher Hits@K and MRR scores due to the powerful representation ability of tucker decomposition. However, TuckER obtains the worst score on the MR metric in Table 3; we argue that the baseline performance may vary among different instances. We further observe that baselines based on textual embeddings such as KG-BERT and StAR are not competitive here. For OpenBG500-L, we notice that vanilla TransE can yield better performance than most of the sophisticated baselines, which indicates that more works should be investigated for large-scale KG representation learning.

2) Multi-modal Link Prediction. The experimental results in Table 3 show that the RSME achieves the best scores except on MR metric, indicating its advanced multi-modal information fusion ability. MKGformer can yield better results on MR metric but achieve comparable performance with RSME.

3.5 Distribution and Maintenance

OpenBG benchmarks were released before submitting to EMNLP 2022 together with an online competition. Up to now, more than 4,043 researchers have applied OpenBG benchmarks, and over 3,000 teams have signed up for the competition.

4 Discussion and Conclusion

4.1 Lessons Learned

Naturally, there are three lessons to be noted when building a business KG. (1) First, everything follow the business logic. Note that practical applications impose constraints on the links in KG by defining an ontology coupled with business logic. Building an accurate, unambiguous, easy-to-maintain, and scalable ontology not only requires developers to have a deep understanding of the business logic but also having a specific prediction of possible future changes so that the design can be close to the status quo and efficient. (2) Second, practical and minimal. Since not all knowledge is necessary for downstream tasks and there exist many wrong facts in the raw corpus; thus, it is important to integrate valuable nodes (e.g., images are valuable for product alignment) rather than all information to KG. (3) Third, quality control is a lifelong work. There are many considerations around the integrity of new knowledge, checking quality, and correcting wrong facts. Moreover, it is critical to managing to change ontology without creating inconsistencies with the knowledge already in the system.

4.2 Conclusion

In this work, we construct and publish OpenBG, an open business knowledge graph derived from a deployed system. To the best of our knowledge, it is the most comprehensive product KG available on the Web. In the future, we will keep developing and improving OpenBG, and hopefully it can benefit KG construction in other vertical domains.
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A Resource Details

A.1 Statistics

The detailed statistics of the ongoing OpenBG in current version is shown in Table 5.

| Core Class Concept | # level1 | # level2 | # level3 | # level4 | # level5 | # ALL / # leaf |
|---------------------|----------|----------|----------|----------|----------|---------------|
| Category            | 93       | 889      | 3,069    | 3,049    | /        | 7,100 / 3,399 |
| Brand               | 45       | 411,234  | /        | /        | /        | 411,279 / 411,234 |
| Place               | 208      | 266      | 333      | 2,847    | 30,773   | 42,426 / 38,069 |
| Scene               | 19       | 4,027    | 617      | 729      | 5,992    | 5,170         |
| Crowd               | 8        | 57       | 45,105   | 57       | /        | 45,207 / 45,180 |
| Theme               | 14       | 5,219    | 143      | 143      | /        | 5,319 / 5,380  |
| Time                | 3        | 55       | /        | /        | /        | 58 / 55       |
| Market_S            | 614,598  | /        | /        | /        | /        | 614,598 / 614,598 |

Overall

- # core classes: 460,805
- # core concepts: 670,774
- # relation types: 2,681
- # products (instances of categories): 3,062,313
- # triples: 2,603,046,837

Table 5: Statistics of OpenBG at the time of writing.

A.2 Cases

We also show cases of OpenBG in Figure 4.

A.3 Process of Building

We illustrate the process of building OpenBG benchmarks in Figure 5.

A.4 Relation Distribution

Relation distributions of OpenBG500 and OpenBG500-L are depicted in Figure 6.
B Baselines Details

We adapt our benchmark settings into the reference models as baselines. In detail, we modify the source code of OpenKE (Han et al., 2018) to implement the TransE, TransH, TransD, DistMult, and ComplEx model. To get the results of TransAE, we refer to the implementation in ksolaiman/TransAE on GitHub. We conduct all the experiments on one NVIDIA TESLA V100 32G GPU utilizing PyTorch. The tuned hyperparameters for each of the model on every dataset are detailed as follows.

**OpenBG-IMG**
- **TransE**
  - num batches: 100
  - num epochs: 1000
  - learning rate: 0.5
  - embedding dimension: 200
  - optimizer: SGD
- **TransH**
  - num batches: 100
  - num epochs: 1000
  - learning rate: 0.5
  - embedding dimension: 200
  - optimizer: SGD
- **TransD**
  - num batches: 100
  - num epochs: 1000
  - learning rate: 1.0
  - embedding dimension: 200
  - optimizer: SGD
- **DistMult**
  - num batches: 100
  - num epochs: 1000
  - learning rate: 0.5
  - embedding dimension: 200
  - optimizer: AdaGrad
- **ComplEx**
  - num batches: 100
  - num epochs: 1000
  - learning rate: 0.5
  - embedding dimension: 200
  - optimizer: AdaGrad
- **TuckER**
  - batch size: 200
  - num epochs: 500
  - learning rate: 5e-4
  - embedding dimension: 200

**OpenBG500**
- **TransE**
  - num batches: 100
  - num epochs: 1000
  - learning rate: 0.5
  - embedding dimension: 200
- **TransH**
  - num batches: 100
  - num epochs: 1000
  - learning rate: 0.5
  - embedding dimension: 200
- **TransD**
  - num batches: 100
  - num epochs: 1000
  - learning rate: 1.0
  - embedding dimension: 200
  - optimizer: SGD
- **DistMult**
  - num batches: 100
  - num epochs: 1000
  - learning rate: 0.5
  - embedding dimension: 200
  - optimizer: SGD
- **ComplEx**
  - num batches: 100
  - num epochs: 1000
  - learning rate: 0.5
  - embedding dimension: 200

**StAR**
- batch size: 32
- num epochs: 7
- learning rate: 1e-5

**RSME**
- batch size: 100
- max epochs: 100
- learning rate: 5e-2
- AdaGrad

**MKGformer**
- batch size: 128
- max epochs: 50
- learning rate: 6e-5

**TransAE**
- num batches: 100
- num epochs: 1000
- learning rate: 0.5
- embedding dimension: 200
- optimizer: SGD

**KG-BERT**
- batch size: 500
- num epochs: 5
- learning rate: 3e-5
- embedding dimension: 200
- optimizer: AdaGrad

• **TuckER**
  - batch size: 200
  - num epochs: 500
  - learning rate: 5e-4
  - embedding dimension: 200

• **KG-BERT**
  - batch size: 500
  - num epochs: 5
  - learning rate: 1e-4
  - embedding dimension: 200

**OpenBG500-L**

• **TransE**
  - num batches: 500
  - num epochs: 100
  - learning rate: 0.5
  - embedding dimension: 200
  - optimizer: SGD

• **TransH**
  - num batches: 1000
  - num epochs: 1000

- learning rate: 0.5
- embedding dimension: 200
- optimizer: SGD

• **TransD**
  - num batches: 1000
  - num epochs: 1000
  - learning rate: 1.0
  - embedding dimension: 200
  - optimizer: SGD

• **DistMult**
  - num batches: 500
  - num epochs: 200
  - learning rate: 0.5
  - embedding dimension: 200
  - optimizer: AdaGrad

• **ComplEx**
  - num batches: 1500
  - num epochs: 200
  - learning rate: 0.5
  - embedding dimension: 200
  - optimizer: AdaGrad