Interactive Visual Exploration of Knowledge Graphs with Embedding-based Guidance

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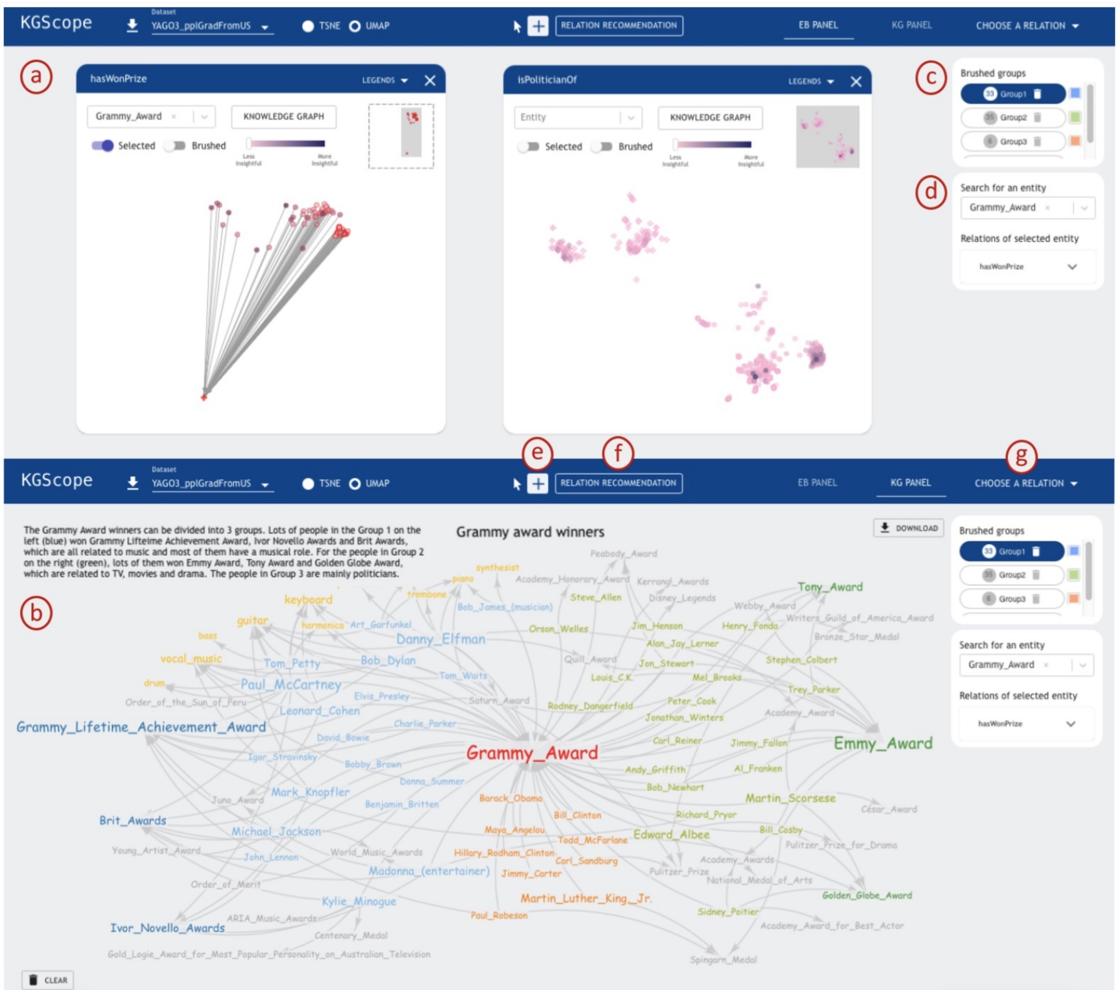

Figure 1: The interface of KGScope. (a) Embedding panel. (b) Multi-relation knowledge graph panel. (c) Brushed groups panel. (d) Related relation panel. (e) Brush tool. (f) Relation Recommendation. (g) Schema panel. In this particular example, the user found that the Grammy award winners can be categorized into three groups: (1) musicians, (2) actors, (3) politicians.

ABSTRACT

Knowledge graphs have been commonly used to represent relationships between entities and utilized in the industry to enhance service qualities. As knowledge graphs integrate data from a variety of sources, they can also be useful references for human users. However, there is a lack of effective tools for data analysts to make the most of the rich information in knowledge graphs. Existing knowledge graph exploration systems are ineffective because they didn't consider various users' needs and the characteristics of knowledge graphs. Exploratory approaches specifically designed for uncovering and summarizing insights in knowledge graphs have not been well studied yet. In this paper, we propose KGScope that supports interactive visual explorations and provides embedding-based guidance to derive insights from knowledge graphs. We demonstrate KGScope with a usage scenario and assess its efficacy in supporting knowledge graph exploration with a user study. The results show that KGScope supports knowledge graph exploration effectively by providing useful information and aiding comprehensive exploration.

CCS CONCEPTS

• **Human-centered computing → Visualization systems and tools**.

KEYWORDS

Knowledge graph, Interactive visual exploration, Knowledge graph embedding

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1 INTRODUCTION

A knowledge graph is a data model that represents the abundant relational information among real-world entities. There are several well-known knowledge graphs in the world, e.g., Google Knowledge Graph [27], DBpedia [17] and YAGO [23]. They have become important resources to support applications in the retail, entertainment, education, or healthcare industries [3, 6, 18]. Besides leveraging knowledge graphs for more accurate recommendations or better service quality of applications, information in knowledge graphs can also be useful for data analysts to reason about and derive insights [20, 25, 28, 33].

To assist users in exploring knowledge graphs, existing systems mainly provide query or search interfaces for their users to start the exploration, where the users are implicitly assumed to understand the data at hand or have particular objectives. In addition, current visualization systems do not support in-depth analysis tools that are applicable to knowledge graphs. For example, they do not make use of the entity embeddings that reveal the semantic similarity between entities, and do not provide proper guidances.

In this work, we propose KGScope, a visualization system that enables users to interactively explore knowledge graphs with three kinds of hints: (a) peculiarity, (b) relation recommendation, (c) similarity. Specifically, we exploit knowledge graph embeddings to measure the peculiarities of entities (Section 4), provide context through schema and embedding visualization, and recommend relations for analyses. Besides the guidance, we utilize several visual designs and interactions, including brushing and linking, to support the entire workflow for users to draw insights from knowledge graphs (Section 5).

We demonstrate the usage and generalizability of KGScope with different types of knowledge graphs in the usage scenarios (Section 6) and validate the efficacy of KGScope through analyzing participants' behaviors and feedback in the user study (Section 7). The results show that KGScope effectively supports knowledge graph explorations in two aspects: (1) aiding participants in conducting comprehensive explorations with convenience and efficiency; (2) providing useful information to assist participants in understanding the data and guide them to find interesting insights.

Concretely, this paper makes the following contributions: (1) We propose KGScope that aims at enabling data analysts to explore knowledge graphs and extract insights. (2) Based on knowledge graph embedding, we design metrics for measuring peculiarities of entities and recommending relations to guide users in exploring knowledge graphs. (3) We demonstrate the effectiveness of exploiting knowledge graph embeddings in visual analytics.

2 RELATED WORK AND BACKGROUND

Knowledge graph exploration. There are many existing works on exploration of networks [5, 8], multivariate and heterogeneous graphs [9, 10, 14, 37], and linked data [15]; however, most of them are not designed for exploring knowledge graphs [26]. Several systems adopted graph-based visualizations to explore knowledge graphs due to their underlying structure [2]. RelFinder [13] automatically extracts the relationships between two entities of users' interest in the knowledge graph and visualizes them as a force-directed graph. The method concentrate on visualizing the structure without supporting in-depth analysis, such as accessing the relative similarities between entities, for users to derive insights efficiently. ALOHA [12] and EduVis [33] target at visually analyzing knowledge graphs in certain domains, and provide gadgets to filter the graph and contrast the analysis. As these works strive to deal with particular tasks for users with explicit purpose, the designed features are mainly applicable to specific knowledge graphs.

Data exploration through embedding visualization. There have been systems designed to interactively explore and analyze objects using the notion of embeddings in other domains, including natural language processing [1, 21], information retrieval [30], and general embedding visualization tool [22, 32]. However, these works do not focus on visual exploration of knowledge graphs. We take advantage of knowledge graph embeddings to provide guidance for

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users who want to explore knowledge graphs and extract insights about the data itself.

Background on knowledge graph embeddings. To facilitate the exploration of such data, we propose to exploit knowledge graph embeddings [7, 39]. A knowledge graph is a multi-relational graph consisting of nodes (representing *entities*) and different types of edges (representing *relations*). Each edge represents a triple denoted by (h, r, t), where h is a head entity, r a relation, and t a tail entity. Given a knowledge graph, its graph embedding computation starts with initially representing entities and relations as multidimensional real-valued vectors. A score function is defined to measure the plausibility of a triplet in the knowledge graph. A triplet with a higher score is more likely to be a fact. The embeddings of relations and entities are learned by optimizing a loss function which is designed to assess the credibility of all the training triplets. The main idea is to represent entities and relations in a vector space while preserving the semantic information in the knowledge graph, which can be used to quantify the relationships between entities.

3 DESIGN REQUIREMENTS

Based on previous studies and surveys on visualization and knowledge graph exploration [16, 20, 31, 35, 40], we identify a set of design requirements for KGScope.

R1. Provide guidance to extract findings: In exploratory tasks, users are usually not familiar with the dataset and have indefinite goals. The design should be able to guide the user in their exploration journey towards the interesting parts of the graph [20].

R2. Ensure awareness of the context: Systems should help the users keep track of the overall context as asking them to memorize the context produces additional cognitive loads [35]. Also, new meanings can be brought to the observation with context information at hand, and this is when insights occur [16].

R3. Facilitate analysis from different perspectives: Entities may form distinct associations when being considered in the context of different relations [40]; however, when analyzing numerous entities at once, showing all relations of every entity in a view could overwhelm users [35]. Therefore, systems should enable users to view and entities from multiple relations while maintaining effective visualization, and allow comparison between multiple relations.

R4. Promote analysis in groups: Besides inspecting individual entities, entities are often analyzed in groups [31]. For users who do not have any clues in advance, through observing the data, they may gain interest in the cluster of entities grouped by the visualization. Moreover, users may want to compare multiple groups of entities as well. Effective exploration tools should be able to pick out groups of entities on demand, reveal possibly related information, and reduce irrelevant data.

4 PECULIARITY GUIDANCE

To reveal unexpected information as one of the exploration guidance, we propose *peculiarity* as a measure of unexpectedness for entities or relations. Suppose that a knowledge graph embedding has learned the behaviors of the majority, which are also the expectations of users. Then, we consider that an entity e is *peculiar* if an embedding model cannot predict its head or tail entities accurately, e.g., predicting a head entity h given a relation r and a tail entity t, denoted as $(?, r, t)$, and vice versa. This kind of prediction is called *link prediction* [29, 38], which is commonly used to evaluate the quality or performance of a knowledge embedding model.

Formally, let $Rel(e)$ be the set of all relations involved with an entity e in a KG. If e is a head entity in a relation $r \in Rel(e)$, then $\mathcal{T}(e, r) = \{t_i | i \in [1, T_{e,r}]\}$ is the set of the tail entities that e links to in r, where $T_{e,r}$ is the number of entities in $\mathcal{T}(e, r)$. For every tail entity t' in r, the score of (e, r, t') is calculated based on the score function of a given knowledge graph embedding eb. After sorting all the candidates by their scores in descending order and applying the filter setting, we obtain the adjusted rank of (e, r, t_i) predicted by eb, $\hat{R}^{(t)}_{eb}(t_i|e, r)$. For the detailed calculation of the filter setting and adjusted rank, please refer to the supplementary materials. Similarly, when e is a tail entity in relation r that links to $H_{e,r}$ head entities, $\mathcal{H}(e, r) = \{h_i | i \in [1, H_{e,r}]\}$, the adjusted rank of (h_i, r, e) when performing head prediction by eb is $\hat{R}^{(h)}_{eb}(h_i|e, r)$. The peculiarity of e in r is defined as follows:

$$P_{eb}(e, r) = \frac{1}{T_{e,r} + H_{e,r}} \left(\sum_{i=1}^{T_{e,r}} \frac{1}{T_r} \hat{R}^{(t)}_{eb}(t_i|e, r) + \sum_{i=1}^{H_{e,r}} \frac{1}{H_r} \hat{R}^{(h)}_{eb}(h_i|e, r) \right), \tag{1}$$

where T_r and H_r are the total number of tail and head entities in r, respectively. We consider the ranks of both head and tail in the peculiarity measure, and because the numbers of the heads and tails in r may not be the same and the interpretation of ranks depends on the number of candidates, the adjusted ranks are normalized before averaged.

As existing embedding models emphasize on encoding different kinds of relations between entities, the link predictions of an entity by different models may vary. Therefore, we utilize a set of embedding models $EB = \{TransR$ [19], $RotatE$ [34], $AttH$ [4]$\}$ to capture patterns in a variety of knowledge graphs and discover truly peculiar entities. Analysis of the peculiarities given by different embeddings can be found in the supplementary materials. Other embedding models can also be included in the set. We take every embedding model into account by summing up $P_{eb}(e, r)$ for all eb in EB to get the peculiarity of e in r, i.e., $P(e, r) = \sum_{\forall eb \in EB} P_{eb}(e, r)$. From an exploratory perspective, all the information related to an entity should be considered when evaluating the peculiarity of the entity. Thus, we sum up $P(e, r)$ for all relations linked to e to obtain its peculiarity, i.e., $P(e) = \sum_{\forall r \in Rel(e)} P(e, r)$. One may think that $P(e)$ could cause a bias that an entity with more relations tends to have a higher peculiarity. However, an entity with more relations indeed also contains more information. Therefore, such an entity still deserves a higher peculiarity.

5 PROPOSED SYSTEM: KGSCOPE

5.1 Context of knowledge graphs

KGScope visualizes two kinds of information to provide the context of a knowledge graph. First, the schema of the knowledge graph (Fig. 2) gives users a high-level structural understanding and statistical hints by displaying all relations and entity types. Users can get an overview of the underlying data and then click on an edge of interest to start the exploration from the corresponding relation.

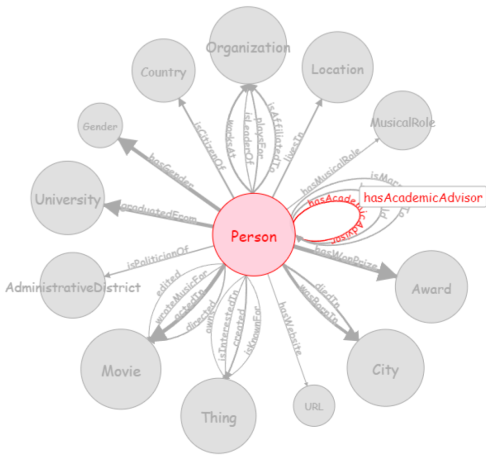

Figure 2: Hovering on the relation, "hasAcademicAdvisor", in the schema panel of YAGO-US-Graduates.

The second kind of context is the proposed *embedding view* (EBView). Given a knowledge graph model, for every relation, each entity is mapped to a high-dimensional vector using a knowledge graph embedding model. Then, for each relation, we employ the dimension reduction technique, UMAP [24], to project the high-dimensional embedding vectors onto a two-dimensional space and visualize them in a scatter plot which we called EBView (Fig. 1(a)). In the EBView, the entities are color-encoded according to the peculiarity (section 4).

The contextual information can act as a type of guidance in KGScope for users to obtain semantically similar or dissimilar entities through observing the relative distances between them. These features satisfy **R1**, **R2** & **R3**.

5.2 Group analysis

KGScope supports exploration tools for three types of groups: (1) *keyword group*, which is formed by the entities with similar keywords and can be found using the search box in KGScope; (2) *sibling group*, which is composed of the entities linked to a common entity in a relation and can be identified in KGView after choosing an entity (Fig. 1 (a)); (3) *visual group*, which is formed by the entities grouped by the EBView (Fig. 3) using the brushing tool manually. Also, various groups can be formed in the EBView with the focusing and filtering tools provided in KGScope. To exclude irrelevant information in groups, users can zoom in, turn on the toggle to only show the selected/brushed entities and the entities linked to them, or filter out entities with peculiarities lower than a specified threshold.

To analyze a group of entities from different perspectives, multiple EBViews are displayed simultaneously so that users can handily compare between relations. The EBViews are accompanied with a brushing-and-linking tool, and with which, when selecting a group of entities in one view, the selected entities in other views will also be highlighted.

KGScope establishes a group-friendly environment to assist users in probing into entity groups. These features satisfy **R3** & **R4**.

5.3 Relation recommendation based on contextual similarity

As KGScope enables and promotes doing analysis on entity groups, recommendation of (interesting) relations for a group of entities is also supported. Since the distance of two entities in a knowledge graph embedding reflects their similarity, we also utilize the embedding for measuring the similarity. However, instead of directly measuring the similarity within a group of entities G, we propose *contextual similarity*, which measures the similarity of other entities connected to G. This centers on the concept that **every entity in the knowledge graph is defined by the connections related to it** and can assist users in finding the commonalities efficiently.

$$S_G(r) = -\left(\sum_{\forall x,y \in G', x \neq y} d(x,y)\right) \Big/ \left(\frac{|G'| \times (|G'|-1)}{2}\right), \quad (2)$$

where $d(x,y)$ is the Euclidean distance between entities x and y in the graph embedding of r; G' denotes all the entities linked to G in relation r; $|G|$ and $|G'|$ are the number of entities in G and G', respectively. The recommended relations are sorted by the similarity scores in a descending order. These features satisfy **R1**, **R3** & **R4**.

5.4 Interpretation and summarization of linking patterns

Despite the efficiency of the EBPanel for providing the global view to assist users in navigating through entities, the relationships between entities may not be intuitively interpreted in the panel. To better derive insights, each EBView (Fig. 3) is accompanied with a corresponding knowledge graph view (KGView) (Fig. 4) with the force-directed layout [11] to reduce occlusion. The size of the text label encodes the sum of the indegree and outdegree of an entity. KGScope offers another option to encode entities of different groups with differ colors. Furthermore, to summarize the observations during the exploration, users can save the KGView they consider intriguing, and the subgraphs will be integrated into the multi-relation knowledge graph panel (MRKGPanel) (Fig. 1(b)). These features satisfy **R2** & **R3**.

6 USAGE SCENARIO

We demonstrate a usage scenario to show how KGScope meets user demands on discovering insights from the *YAGO3-US-Graduates* [23] knowledge graph (43,193 triplets, 15,632 entities, and 25 relations). Additional information on data preparation and more usage scenarios can be found in supplementary materials.

We search for "Grammy Award" in the search box to initiate the exploration. By observing the EBView of relation "hasWonPrize", we roughly identify three groups among the awardees (Fig. 3). We brush them separately and inspect them in the KGView. Through interpreting the names of the entities, it is surprising that the entities in the third group are mainly politicians (see also the orange entities in Fig. 1(b)) and they also have higher peculiarity values. For the other two groups, we cannot immediately differentiate between them through their names; thus, we inspect the other awards they have won. The KGView of the first group (Fig. 4(a)) shows that other awards they have won are Grammy Life Time Achievement

Award, Ivor Novello Award, and Brit Award, which are related to music. For the second group, other awards they won include Emmy Award, Tony Award, and Golden Globe Award, which are related to TV, theater, and film industry (Fig. 4(b)). It appears that group 2 are actors. All the views that are saved during exploration are summarized in the MRKGPanel (Fig. 1(b)).

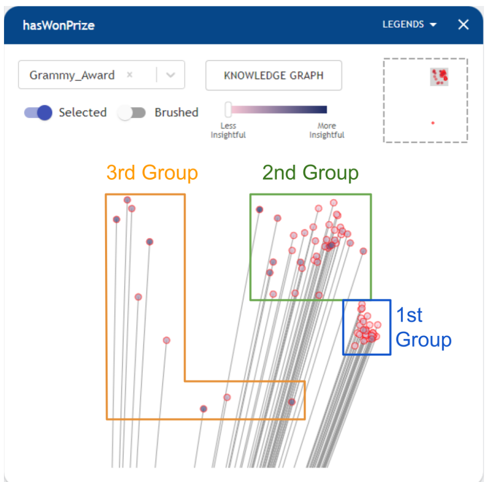

Figure 3: The distributions of Grammy Award awardees in the embedding view.

Besides "hasWonPrize", we also explore if the 3 groups can be distinguished in other relations. Since we have no idea of which relation to examine, we refer to the relations recommended by KGScope for the first group. We examine the relation, "hasMusicalRole", which is ranked second in the recommendation with 23 entities in it. The people in the first group have musical roles like vocal music, keyboard, guitar, etc (Fig. 5). When we switch to the second group, we find that none of them has a musical role. This again confirms our previous findings that the Grammy Award winners can be divided into 3 groups: musicians, actors, and politicians. The colors in the MRKGPanel allow us to recognize different groups and wrap up our findings efficiently. This scenario shows that KGScope facilitates doing group analysis and the relation recommendation enables users to find commonalities of a group, which may further distinguish between groups.

7 USER STUDY

We conducted a user study to compare KGScope with a baseline system, and investigated how the user experiences and the exploration findings are improved with the features supported by KGScope.

7.1 Study protocol

7.1.1 Baseline. We designed a system which imitates existing knowledge graph exploration systems as the baseline. Fig. 6 shows the interface of the baseline. It is a simplified version of KGScope where the EBPanel, the relation recommendation panel, and the brush groups panel are removed. Besides, the drop down menu of the entity search box and the relations in the related relation panel in the baseline are randomly ordered. Users can incrementally expand the graph by clicking the nodes in the graph or select entities from the search box and then select relations to expand. The knowledge graph data is also visualized as a force-directed graph. At the end, users can wrap up their insights in the same view where they explore the knowledge graphs. The baseline is akin to the existing systems that mainly offer exploration of the raw data without guidance or context.

7.1.2 Datasets and Participants. We used four datasets, *YAGO3-US-Graduates*, *TMDB-After-2000*, *KG20C* [36], and *Marvel KG*, from different domains including Wikipedia, movies, academia, and comics, respectively. For more details, please refer to supplementary materials. We recruited 12 post-graduate students (5 females and 7 males, average age 23.5) who have experience in data analysis. The average self-reported familiarity with data exploration/analysis on a 5-point scale (1 for "no experience at all" and 5 for "doing almost everyday") was 3.5 (σ=1.3). All participants were screened to make sure that they had neither explored the study datasets before, nor had they used the baseline and KGScope.

7.1.3 Procedure. We adopted a within-subject design where each participant conducted one exploratory session with Baseline and another one with KGScope, on the same dataset. *Marvel KG* is only used for practice before the formal experiments. The other 3 datasets are evenly distributed among the 12 participants according to their preferences. At the end, each dataset is explored by 4 participants. The order of the systems each participant used was counterbalanced to avoid bias.

In each session, participants practiced using the system for 10 minutes, then, two general tasks were given to the participants in the formal study. On Task 1, each participant conducted an open-ended exploration on the dataset for 15 minutes. On Task 2, every participant was first asked to choose an entity e of his/her own interest and it should be connected to more than one entities in some relation r. Then, the participant explored the entities linked to e in r for 10 minutes. This task was used to investigate a participant's behavior in focused explorations of a sibling group. Participants were asked to think aloud during their explorations and summarize the insights they found by typing the descriptions in the systems at the end of each task. After the two sessions, participants filled out the post-test questionnaires and had interviews. Each participant spent approximately 2 hours to complete the experiment.

Each participant's audio, screen and interaction logs of were recorded. The post-test questionnaire included 6 questions for the usability of both systems (in 5-point Likert scale ratings) and the rationales for the ratings. The post-test questionnaire can be found in supplementary materials.

7.2 Results

7.2.1 Usability. As shown in Fig. 7, the participants gave significantly higher ratings ($p < 0.05$) on KGScope than the baseline in all questions except Q1. They perceived that KGScope and the baseline offer similar support on open-ended explorations (Q1), but KGScope obviously excelled at focused explorations (Q2). Participants considered the information provided by KGScope useful in helping them decide which parts of the data to explore (Q3), in

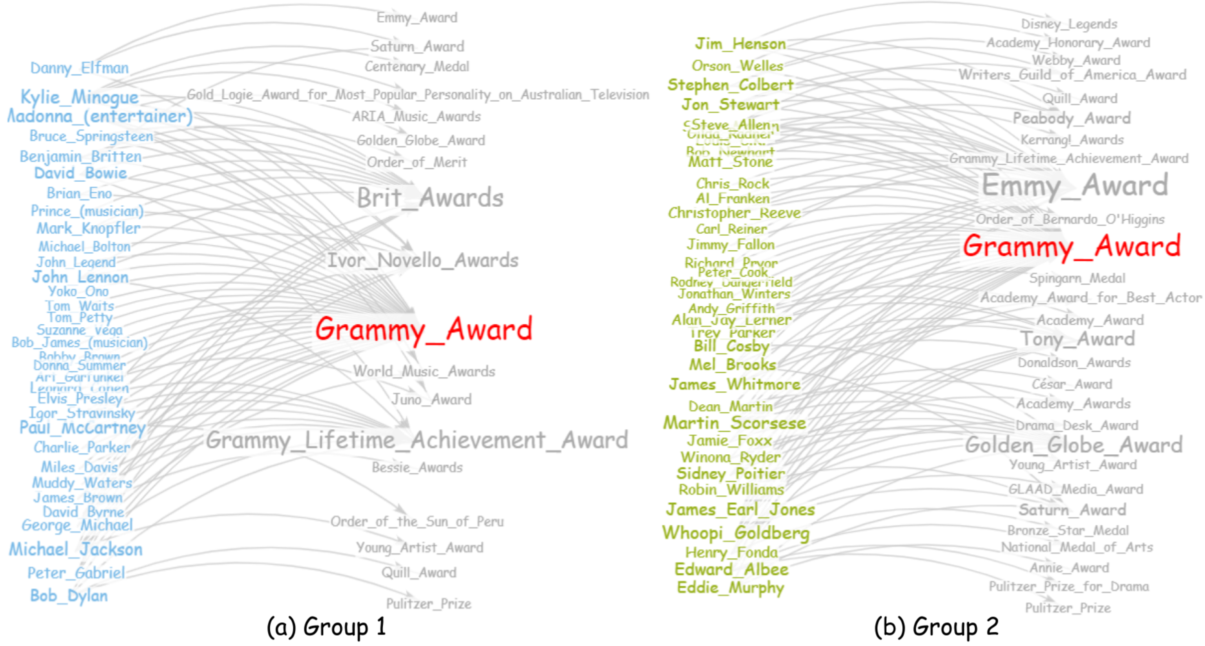

Figure 4: Other awards that the Grammy Award winners have won derived from the group analysis in Fig. 3. It appears that Group 1 is mostly related to musicians, while Group 2 is mainly related to actors.

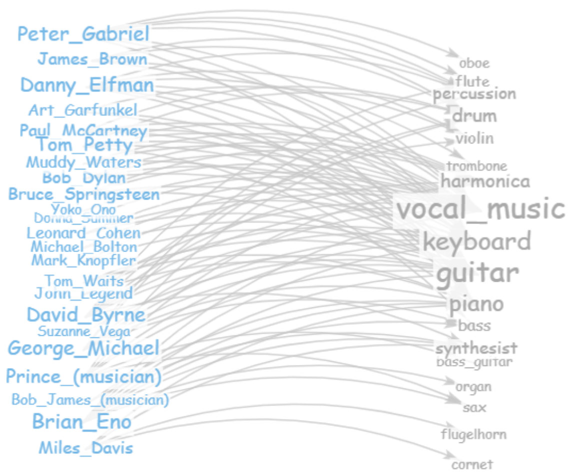

Figure 5: The knowledge graph view of "hasMusicalRole" with Group 1 selected. This confirms that the entities in Group 1 are mostly musicians.

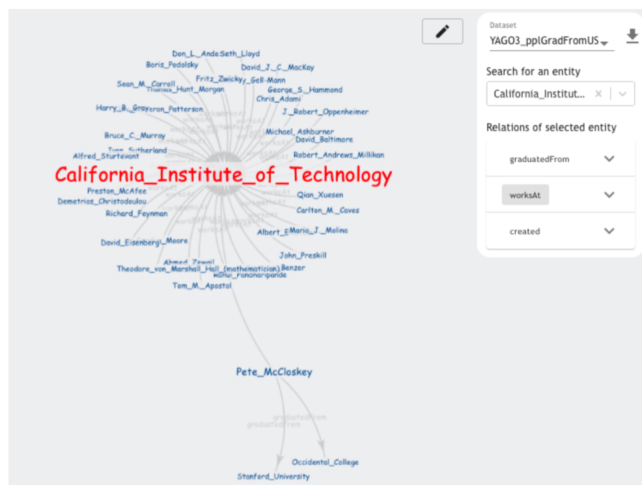

Figure 6: The interface of the baseline system.

interpreting the relations between entities efficiently (Q4), and in wrapping up the explorations with satisfying insights (Q5, Q6).

7.2.2 Behavior analysis. We analyzed the participants' findings with their interaction logs and behavior recordings. It reveals that KGScope allows the participants to: (a) be more willing to explore unknown entities - among the insights related to unknown entities, 3 of them were found with the baseline and 15 of them were found with KGScope; (b) get more findings that are unexpected to the users - among the unexpected findings, 9 were developed with the baseline and 17 with KGScope; (c) explore entities in group and uncover relevant and interesting insights. Comparing KGScope with the baseline, in task 1, 3 out of 12 participants reported groups in their findings when using baseline; on the other hand, 10 out of 12 participants mentioned groups when using KGScope.

7.2.3 Qualitative feedback. Participants reported that KGScope provides useful features, including (a) high-level guiding information to assist understanding of data, (b) visual hints for exploration,

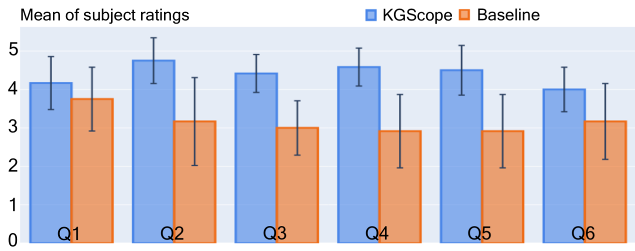

Figure 7: Mean of participants' 5-point Likert scale ratings on the usability of KGScope and baseline (1="strongly disagree" and 5="strongly agree"). Q1. Open-ended exploration; Q2. Focused exploration; Q3. Usefulness of information; Q4. Efficiency of interpretation; Q5. Easiness of wrapping up; Q6. Insight satisfaction. KGScope received significantly higher ratings ($p < 0.05$) than the baseline in all aspects except Q1. The error bar denotes the standard deviation.

(c) helpful recommendations for a comprehensive exploration, and (d) a useful separation of the summarization workspace and the exploration workspace.

8 DESIGN IMPLICATIONS AND CONCLUSION

In knowledge graph exploration, participants considered an observation insightful if it was unexpected or related to the summarization of a set of data, especially the commonalities. To derive intriguing insights, deeper information should be provided and be able to be consumed by users. The information given by the embeddings, including similarities and peculiarities, could be comprehended through the process by guiding participants to conduct breadth-oriented exploration, perform in-depth analysis, and eventually discover satisfying insights.

In conclusion, we introduce KGScope to assist data analysts in exploring knowledge graphs in breadth and depth and further acquiring insights. While formulating design requirements, we take users' needs and knowledge graphs' characteristics into account. With KGScope, users can obtain an overall understanding of the data and be guided to systematically explore the knowledge graph. Recommending relations besides entities enables analysis from different perspectives and reveals fascinating associations. Our user scenario and user study demonstrate the effectiveness and generalizability of KGScope in exploring different knowledge graphs.

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