Orion: Enabling Suggestions in a Visual Query Builder for Ultra-Heterogeneous Graphs

ABSTRACT

The database community has long recognized the importance of graphical query interface to the usability of data management systems. Yet, relatively less has been done. We present Orion, a visual interface for querying ultra-heterogeneous graphs. It iteratively assists users in query graph construction by making suggestions via data mining methods. In its active mode, Orion automatically suggests top-k edges to be added to a query graph. In its passive mode, the user adds a new edge manually, and Orion suggests a ranked list of labels for the edge. Orion's edge ranking algorithm, Random Decision Paths (RDP), makes use of co-occurring edge sets to rank candidate edges by how likely they will match the user's query intent. Extensive user studies using Freebase demonstrated that Orion users have a 70% success rate in constructing complex query graphs, a significant improvement over the 58% success rate by the users of a baseline system that resembles existing visual query builders. Furthermore, using active mode only, the RDP algorithm was compared with several methods adapting other data mining algorithms such as random forests and naïve Bayes classifier, as well as class association rules and collaborative filtering based on singular value decomposition. On average, RDP required 40 suggestions to correctly reach a target query graph (using only its active mode of suggestion) while other methods required 1.5–4 times as many suggestions.

1. INTRODUCTION

The database community has long recognized the importance of graphical query interfaces to the usability of data management systems [6]. Yet, relatively less has been done and there remains a pressing need for investigation in this area [18, 1]. Nevertheless, a few important ideas (e.g., Query-By-Example [35]) and systems (e.g., Microsoft SQL Query Builder) have been developed for querying relational databases [5], web services [28] and XML [11, 29].

For querying graph data, existing systems [9, 13, 22, 21, 8, 17] allow users to build queries by visually drawing nodes and edges of query graphs, which can then be translated into underlying representations such as SPARQL and SQL queries. While focusing on blending query processing with query formulation [13, 22, 21, 8, 17], existing visual query builders do not offer suggestions to users regarding what nodes/edges to include into query graphs. At every step of visual query formulation, after adding a new node or a new edge into the query graph, a user would need to choose from a list of candidate *labels*—names and types for a node or types for an edge. The user, when knowing what label to use, can search the list of labels by keywords or sift through alphabetically sorted options using binary search. But, oftentimes the user does not know the label due to lack of knowledge of the data and the schema. In such a scenario, the user may need to sequentially comb the option list. Furthermore, the user may not have a clear label in mind due to their vague query intent.

The lack of query suggestion presents a substantial usability challenge when the graph data require a long list of options, i.e., many different types and instances of nodes and edges. The aforementioned systems [9, 13, 22, 21, 8, 17] were all deployed on relatively small graphs. The crisis is exacerbated by the proliferation of *ultra-heterogeneous graphs* which have thousands of node/edge types and millions of node/edge instances. Widely-known ultra-heterogeneous graphs include Freebase [10], DBpedia [4], YAGO [32], Probase [33], and various RDF datasets in the "linked open data" [1]. Users would be better served, if graph query builders provided suggestions during query formulation. In fact, query suggestion has been identified as an important feature-to-have among the desiderata of next-generation visual query interfaces [7].

This paper presents Orion, a visual query builder that provides suggestions, iteratively, to assist users formulate queries on ultra-heterogeneous graphs. A demonstration video of the current system is available at https://www.youtube.com/watch?v=3p5xWX5WnS4. Orion's graphical user interface allows users to construct query graphs by drawing nodes and edges onto a canvas using simple mouse actions. To allow schema-agnostic users to specify their exact query intent, Orion suggests candidate edge types by ranking them on how likely they will be of interest to the user, according to their relevance to the existing edges in the partially constructed query graph. The relevance is based on the correlation of edge occurrences exhibited in various sources such as the data graph itself, external textual sources, and user query logs. To the best of our knowledge, Orion is the first visual query formulation system that automatically makes ranked suggestions to help users construct query graphs.

Orion supports both an *active* and a *passive* operation mode. (1) If the canvas contains a partially constructed query graph, Orion operates in the active mode by default. The system automatically recommends top-k new edges that may be relevant to the user's query intent, without being triggered by any user actions. Figure 1(a)

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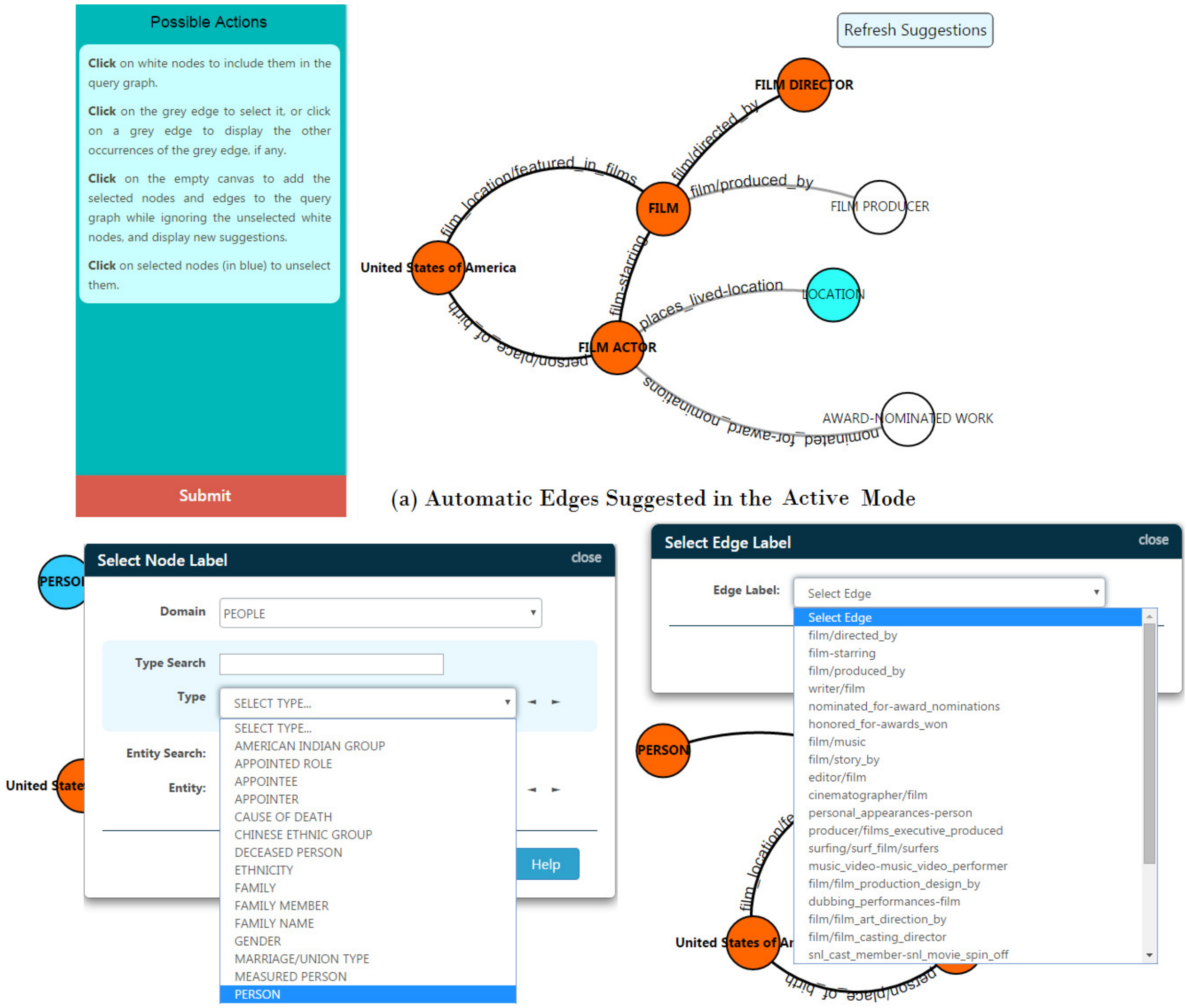
[1] Linking open data. http://www.w3.org/wiki/SweoIG/TaskForces/CommunityProjects/LinkingOpenData.



(a) Automatic Edges Suggested in the Active Mode

(b) Adding a Node in the Passive Mode

(c) Adding an Edge in the Passive Mode

Figure 1: User Interface of Orion

shows the snapshot of a partially constructed query graph, with nodes and edges suggested in the active mode. The white nodes and the edges incident on them are newly suggested. The user can select some of the suggested edges by clicking on them, and a mouse click on the canvas adds the selected edges to the partial query graph, and ignores the unselected edges. (2) The passive mode is triggered when the user adds new nodes or edges to the partial query graph using simple mouse actions. For a newly added edge, the suggested edge types are ranked based on their relevance to the user's query intent. Figure 1(c) shows the ranked suggestions, displayed in a pop-up box, for the newly added edge between the two nodes of types Person and Film from Figure 1(a). For a newly added node, labels are suggested for its type, the domain of its type, and its name if the node is to be matched with a specific entity. The suggested labels are displayed in a pop-up box, as shown in Figure 1(b), where type Person is chosen as the label for the node.

The query construction process of a user can be summarized as a query session, consisting of positive and negative edges that correspond to edge suggestions accepted and ignored by the user, respectively. At every step of the iterative process, based on the partially constructed query graph so far and the corresponding query session, Orion's edge ranking algorithm—Random Decision Paths (RDP)—ranks candidate edges using a collection of co-occurring edge sets. RDP ranks the candidate edges by how likely they will be of interest to the user, according to their correlation with the current query session's edges. RDP constructs multiple decision paths using different random subsets of edges in the query session. This idea is inspired by the ensemble learning method of random forests, which uses multiple decision trees. Entries in the co-occurring edge sets that subsume the edges of a decision path are used to find the "support" score of each candidate edge. For each candidate, its support scores over all random decision paths are aggregated into its final score. Section 4.3.2 describes this ranking method in detail. We also implemented several other edge ranking methods by adapting data mining algorithms such as random forests (RF) and naïve Bayes classifier (NB), as well as class association rules (CAR) and collaborative filtering based on singular value decomposition (SVD). Section 4.2 describes these techniques in detail.

For ranking candidate edges, RDP and all the baseline methods draw evidence from a collection of co-occurring edge sets. We proposed several approaches to obtaining such co-occurring edge sets, from the data graph itself, textual sources such as Wikipedia, and user query logs. Regardless of which of these data sources is used, their commonality is that they provide insights on which edges (or corresponding relationships) are used together in forming queries (or writing articles) or possessed together by entities. Such co-occurrence information gives evidence useful to rank candidate edges by their relevance to the user's query intent. Section 5 describes these approaches in detail. Once Orion is in use, query sessions collected by it would result in a real-world query log that can contribute to the community in this line of research.

We conducted extensive user studies over the Freebase data graph, using 30 graduate students from the authors' institution, to compare Orion with a baseline system that resembles existing visual query builders. Half of the participants used Orion, and the other half used the baseline system. A total of 105 query tasks were performed by users of each system. It was observed that Orion users had a 70% success rate in constructing complex query graphs, significantly better than the 58% success rate of the baseline system's users. We also conducted experiments on both Freebase and DBpedia data graphs to compare RDP with other edge ranking methods—RF, NB, CAR and SVD. The experiments were executed on the resources of a United States federally-funded large-scale computing infrastructure, [2] to accommodate memory-intensive methods such as RF, SVD and CAR, which required between 40 GB to 100 GB of memory. On average, the other methods required 1.5-4 times more suggestions to complete a query graph, compared to RDP's 40 suggestions. The wall-clock time required to complete query graphs by RDP was mostly comparable with that of RF and NB, and significantly less than that of SVD and CAR. We also performed experiments to study the effectiveness of the co-occurring edge sets generated using various approaches. RDP attained higher efficiency with the Wikipedia-based co-occurring edge sets compared to other ways discussed in Section 5.

We summarize the contributions of this paper as follows:

- We present Orion, a visual query builder that helps schema-agnostic users construct query graphs by making automatic edge suggestions. To the best of our knowledge, none of the existing visual query builders for graphs offers suggestions.
- To help users quickly construct query graphs, Orion uses a novel edge ranking algorithm, Random Decision Paths (RDP), which ranks candidate edges by how likely they will be relevant to the user's query intent. RDP is trained using a collection of co-occurring edge sets.
- We proposed several approaches of generating co-occurring edge sets. This is important, as there exists no publicly available query logs from visual query builders. Once Orion is in use, the real-world query log collected by it will become a valuable resource to the community.
- We conducted user studies on the Freebase data graph to compare Orion with a baseline system that resembles existing visual query builders. Orion had a 70% success rate of constructing complex query graphs, significantly better than the baseline system's 58%.
- We also performed extensive experiments comparing RDP with several other data mining based methods, on the Freebase and DBpedia data graphs. Other methods required 1.5–4 times more suggestions than RDP, in order to complete query graphs.

2. RELATED WORK

The unprecedented proliferation of linked data and large, heterogeneous graphs has sparked extensive interest in building knowledge-intensive applications. The usability challenges in such applications are widely recognized—declarative query languages such as SPARQL present a steep learning curve, as forming queries requires expertise in these languages and knowledge of data schema. To tackle the challenges, a number of alternate querying paradigms for graph data have been proposed recently, including keyword search [15, 14], query-by-example [19, 20, 23, 26], natural language query [34], and faceted browsing [3, 27, 16].

Visual query builders [13, 30, 22, 21, 8, 17] provide an intuitive and simple approach to query formulation. Most of these systems deal with querying a graph database and not a single large graph, except [17, 13, 30]. Firstly, it is unclear how to directly apply the techniques proposed by systems that deal with graph databases to a single large graph. This is because their solutions work best on a data model with many small graphs rather than a single large graph. Secondly, these systems do not assist the user in query formulation by automatically suggesting the new top-k relevant edges.

QUBLE [17], GRAPHITE [13] and [30] provide visual query interfaces for querying a single large graph. But, they focus on efficient query processing, and only facilitate query graph formulation by giving options to quickly draw various components of the query graph. Instead of recommending query components that a user might be interested in, they alphabetically list all possible options for node labels (which may be extended to edge labels similarly). They also deal with smaller data graphs. For instance, the graph considered by QUBLE contains only around 10 thousand nodes with 300 distinct node types, and they do not consider edge types. Orion, on the other hand, considers large graphs such as Freebase, which has over 30 million distinct nodes and 5 thousand distinct edge types. With such large graphs, it is impractical to expect users to add edges to a query graph by alphabetically browsing through all options and selecting the most appropriate edges. Ranking these edges by their relevance to the user's query intent is a necessity, for which Orion is designed.

3. SYSTEM OVERVIEW

3.1 Data Model and Query Model

An ultra-heterogeneous graph G_d, also called the data graph, is a connected, directed multi-graph with node set $V(G_d)$ and edge set $E(G_d)$. A node is an entity [3] and an edge represents a relationship between two entities. The nodes and edges belong to a set of *node types* T_V and a set of *edge types* T_E, respectively. Each node (edge) type has a number of node (edge) instances. Each node $v \in V(G_d)$ has an unique identifier, a name, [4] and one or more node types $\mathrm{vtype}(v) \subseteq T_V$. Each edge $e = (v_i, v_j) \in E(G_d)$, denoting a relationship from node v_i to node v_j, belongs to a single *edge type* $\mathrm{etype}(e) \in T_E$.

For example, Will Smith and Tom Cruise are instances of node type FILM ACTOR. They are also instances of node type PERSON. There exist an edge (Tom Cruise, Top Gun) and another edge (Will Smith, Men in Black) which are both edges of type *starring*.

The type of an edge constraints the types of the edge's two end nodes. For instance, given any edge $e = (v_i, v_j)$ of edge type *starring*, it is implied that v_i is an instance of node type FILM ACTOR and v_j is an instance of node type FILM, i.e., FILM ACTOR$\in \mathrm{vtype}(v_i)$ and FILM $\in \mathrm{vtype}(v_j)$.

Given a data graph, users can specify their query intent through query graphs. The concept of query graph is in Definition 1. The

[2]Details of the infrastructure are omitted, to comply with double-blind reviewing.

[3]Atomic values such as integers are not supported in the current version of the system.

[4]Without loss of generality and for ease of presentation, we use a node's name as its identifier in presenting examples, assuming the names are unique.

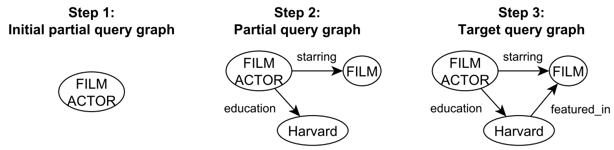


Figure 2: Example Partial and Target Query Graphs

nodes in a query graph are labeled by either the names of specific nodes or node types. Each answer graph to the query graph is a subgraph of the data graph and is edge-isomorphic to the query graph. In the answer graph, a node of the query graph is matched by a node of the specified name or any node of the specified type. For instance, the query graph in Step 3 of Figure 2 finds all Harvard educated film actors who starred in films featuring Harvard. In Figure 2 and other query graphs, the all-capitalized node labels represent node types, while others represent node names.

Definition 1 (Query Graph) A query graph G_q is a connected, directed multi-graph with edge set $E(G_q)$ and node set $V(G_q)$ that may consist of both names and types, i.e.:

- $V(G_q) \subseteq T_V \cup V(G_d)$.
- $\forall e \in E(G_q), \text{etype}(e) \in T_E$. ■

3.2 User Interface for Providing Suggestions

Orion helps users interactively and iteratively grow a partial query graph G_p to a target query graph G_t. It suggests edges to a user and solicit the user's response on the edges' relevance, in order to obtain a G_t that satisfies the user's query intent. The query session ends when either the user is satisfied by the constructed query graph or the user aborts the process. The goal is to minimize the number of suggestions required to construct the target query graph.

Figure 2 shows an example sequence of steps to construct a query graph. The user starts by forming the initial partial query graph G_p consisting of a single node. Step 1 in Figure 2 shows one such G_p with a node of type FILM ACTOR. New edges are then suggested to the user, who can choose to accept some of the suggestions. For instance, step 2 in Figure 2 shows the modified partial query graph obtained after adding two edges (together with two new nodes incident on the edges). Without taking the suggested edges, the user can also directly add a new node or a new edge. The system provides a ranked list of suggestions on the label of the new node/edge, for the user to choose from. Step 3 in Figure 2 shows the example target query graph obtained after adding the edge *featured_in* between Harvard and FILM. In general, to arrive at the target query graph G_t, the user continues the aforementioned process iteratively.

Figure 1(a) shows the user interface of Orion. A demonstration video of the system is also available at https://www.youtube.com/watch?v=3p5xWX5WnS4. Below we explain the major functions and features of the system. We leave more details in the video, to help maintain the readability of the paper. It consists of a query canvas where the query graph is constructed. In its active mode, Orion automatically suggests and displays top-k new edges to add to the partial query graph. The user may not accept the suggestions. Instead, they may use simple mouse actions on the query canvas to add new nodes and new edges. That will let Orion enter the passive mode, in which it ranks candidate node and edge labels and displays them using drop-down lists in pop-up windows as shown in Figures 1(b) and (c). Orion also offers dynamic tips which list all allowable user actions at any given moment of the query construction process, as shown in Figure 1(a).

Active Mode: An Orion user begins the query construction process by adding a single node into the empty canvas. Once the canvas contains a partial query graph consisting of at least a node, Orion automatically operates in its active mode and suggests top-k new edges. Each suggested new edge is between two existing nodes or between an existing node and a new node. Figure 1(a) shows a partial query graph comprised of the four dark nodes and the edges between them. The system suggests top-3 new edges, of which each is between an existing node (dark color) and a new node (white or light color). The user can click on some white nodes (which then become light colored, e.g., LOCATION in Figure 1(a)) to add them to the query graph, and ignore others. The unselected white nodes are removed from display with a mouse click on the canvas, and the next set of new suggestions are automatically displayed. If the user does not want to select any white nodes, a new set of suggestions can be manually triggered by clicking the "Refresh Suggestions" button on the query canvas.

Passive Mode: At any moment in the query construction process, a user can add a node or an edge using simple mouse actions, which triggers Orion to suggest labels for the newly added node/edge, i.e. it operates in the passive mode. **1)** To add a new edge between two existing nodes in the partial query graph, the user clicks on one node and drags their mouse to the destination node. The possible edge types for the newly added edge are displayed using a drop-down list in a pop-up suggestion panel, as shown in Figure 1(c). The edge types are ranked by their relevance to the query intent. **2)** To add a new node, the user can click on any empty part of the canvas. A suggestion panel pops up, as shown in Figure 1(b). It assists the user to select either a name or a type for the node. The options in the two drop-down lists in Figure 1(b), one for selecting names and the other for types, are sorted alphabetically. [5] To help the user find the desired node name or type, the suggestion panel is organized in a 3-level hierarchy. Node types are grouped into domains. The user can choose a domain first, followed by a node type in the domain and, if desired, the name of a specific node belonging to the chosen type. The panel also allows the user to search for desired node name or type using keywords. Right after the new node is added, it is not connected to the rest of the partial query graph. Orion makes sure the partial query graph is connected all the time, except for such a moment. Hence, no other operation is allowed, until the user adds an edge connecting the newly added node with some existing node, by using the aforementioned step 1).

3.3 Candidate Edges

Orion assists users in query construction by suggesting edge types to add to the partial query graph G_p, in both active and passive modes. In its passive mode, a new edge is drawn between nodes v and v' by clicking the mouse on one node and dragging it to the other. The set of candidate edges in the passive mode, C_P, consists of all possible edge types between v and v'. The set of candidate edges in the active mode, C_A, consists of any edge that can be incident on any node in $V(G_p)$, subject to the schema of the underlying data graph. A candidate edge can be either between two existing nodes in G_p, or between a node in G_p and a new node automatically suggested along with the edge.

Definition 2 (Incident Edges) Given a data graph G_d, the incident edges $\text{IE}(v)$ of a node $v \in V(G_d)$, is the set of types of the edges in $E(G_d)$ that are incident on node v. I.e., $\text{IE}(v) = \{\text{etype}(e) | e = (v, v_i) \text{ or } e = (v_i, v), e \in E(G_d)\}$. ■

[5] Orion currently ranks suggested edges by their relevance to users' query intent, in both active and passive modes. Ranking node names/types based on query intent is a future step.

Definition 3 (Neighboring Candidate Edges) Given a partial query graph G_p, the neighboring candidate edges $\mathrm{NE}(v)$ of any node $v \in V(G_p)$, is the set of edge types defined as follows, depending on if v is a specific node name or a node type (cf. Definition 1):
1) if $v \in V(G_d), \mathrm{NE}(v) = \mathrm{IE}(v)$;
2) if $v \in T_V, \mathrm{NE}(v) = \bigcup\{\mathrm{IE}(v')|v' \in V(G_d), v \in \mathrm{vtype}(v')\}$.■

Definition 4 (Candidate Edges) Candidate edges C is the set of types of the possible edges that can be added to the partial query graph G_p at any given moment in the query construction process.

$$C = \begin{cases} C_P = \mathrm{NE}(v) \cap \mathrm{NE}(v') & \text{in passive mode} \\ C_A = \bigcup_{v \in V(G_p)} \{e | e \in \mathrm{NE}(v)\} & \text{in active mode} \end{cases} \quad (1)$$

where v and v' are the two end nodes of a newly added edge in passive mode.

In Section 4 we discuss how to rank candidate edges and thus make suggestions to users in the query construction process.

4. RANKING CANDIDATE EDGES

A simple method to rank candidate edges is to order them alphabetically. A more sensible method is to rank them by using statistics such as candidate edges' frequency in the data graph. Such a query-independent method ignores information regarding users' intent. More specifically, it does not consider the ongoing user query session – the edges that the user has accepted and rejected so far in constructing a query graph. Thus the crux of our technical problem is to define a scoring function $\mathrm{score}_Q(e)$ for measuring the relevance of a candidate edge e to a given query session Q. The concept of query session is defined as follows.

In a user's query session, edges found relevant, accepted and added to the query graph by the user are called *positive* edges. In Orion's active mode, suggested edges that are not accepted by the user are called *negative* edges. Both positive and negative edges play an important role in gauging the user's query intent, as evidenced by our experiments. At any given moment in the query formulation process, the set of all positive and negative edges hitherto forms a query session.

Definition 5 (Query Session) A query session Q is defined as a set of positive and negative edges. T_E (cf. Section 3.1) is the set of all possible positive edges for a data graph G_d. If an edge $e \in T_E$ appears as a negative edge in a query session, it is represented as $\overline{e}$. The set of all possible negative edges, denoted $\overline{T_E}$, is defined as $\overline{T_E} = \cup_{e \in T_E}\{\overline{e}\}$. Let $T = T_E \cup \overline{T_E}$. A query session $Q \in \mathcal{P}(T)$, where $\mathcal{P}(T)$ is the power set of T. [6] ■

4.1 Problem Modeling

The problem of candidate edge ranking, more specifically the task of defining $\mathrm{score}_Q(e)$, can be modeled as several different but highly related data mining operations. Consider the fact that e is a single edge and Q is a set of edges. The problem can be casted as association rule mining, collaborative filtering, and classification, with a few differences. (1) As a classification problem, we are classifying Q, which is modeled as a vector of $|T|$ binary features. Each feature corresponds to a positive or negative edge, of which a value 1 in the vector indicates the existence of the corresponding edge in Q. The class attribute being predicted is the edge suggestion whose domain of values is the candidate edge set C, as defined in Definition 4. What deviates from typical classification tasks is that the class labels and features both come from T. (2) In the setting of association rule mining, a query session Q is an itemset and we assess the strength of rule $Q \rightarrow e$ for each candidate edge e. However, it makes little sense to directly evaluate the strength of such a rule, as there can be few "transactions" (past query sessions) that subsume Q, especially if Q is relatively long. A plausible solution is to discover multiple rules of the form $X \rightarrow e$ from the transactions and apply those rules covered by Q (i.e., $X \subseteq Q$). (3) It can also be viewed as a recommendation problem – Given Q, decide which e to recommend. If there are multiple query sessions, then collaborative filtering as a recommendation technique can be applicable. The gist becomes assessing whether e exists in other query sessions similar to Q and whether edges similar to e are already included in Q. Collaborative filtering typically operates on a n user $\times$ m objects matrix of numeric values. Our problem represents a special case of binary matrix of n query sessions and $|T|$ edges.

Id	Query Session
w_1	*education*, *founder*, $\overline{\textit{nationality}}$
w_2	*starring*, $\overline{\textit{music}}$, *director*
w_3	*nationality*, $\overline{\textit{education}}$, *music*, $\overline{\textit{starring}}$
w_4	$\overline{\textit{artist}}$, $\overline{\textit{title}}$, *writer*, *director*
w_5	$\overline{\textit{director}}$, *founder*, *producer*
w_6	*writer*, $\overline{\textit{editor}}$, *genre*
w_7	$\overline{\textit{award}}$, *movie*, *director*, $\overline{\textit{genre}}$
w_8	*education*, *founder*, $\overline{\textit{nationality}}$

Table 1: Example Collection of Co-occurring Edge Sets W

For calculating $\mathrm{score}_Q(e)$, all these different ways of modeling draw evidence from sets of co-occurring edges, i.e., the training data for classification, the transactions for association rule mining, and the n query sessions in collaborative filtering. We denote a collection of co-occurring edge sets by W. Table 1 shows an example W containing 8 co-occurring edge sets, one per line. For instance, w_4 consists of positive edges *writer* and *director* and negative edges $\overline{\textit{artist}}$ and $\overline{\textit{title}}$.

In Section 5, we discuss several approaches of obtaining such co-occurring edge sets W, from the data graph itself, textual sources such as Wikipedia, and user query logs. Regardless of where W comes from, the commonality of the above-mentioned sources is that they provide insights on which edges (or corresponding relationships) are used together in forming queries (or writing articles) or possessed together by entities. Such co-occurrence information gives evidence useful to rank candidate edges by their relevance to the user's query intent.

Problem Statement: Given a collection of co-occurring edge sets W, an ongoing query session Q and a set of candidate edges C (cf. Equation 1), the problem is to rank the edges e in C by a scoring function $\mathrm{score}_Q(e)$ that captures the likelihood that the user would find them relevant.

In our discussion of scoring methods, we focus on modeling the problem as classification. In Section 4.2, we describe several baseline methods, including classifiers using random forests and naïve Bayes classification, a classification approach based on association rules, and a collaborative filtering approach based on singular value decomposition. In Section 4.3 we propose a novel method inspired by random forests.

[6] Note that not every subset of T forms a valid query session. Specifically, an edge type cannot appear in the form of both a positive edge e and a negative edge $\overline{e}$ in a query session. If an edge has been accepted by the user, then it cannot be rejected at the same time, and vice verse. Hence, the set of valid query sessions is a subset of $\mathcal{P}(T)$. For simplicity of presentation, without loss of generality, we will not make the distinction in the rest of the paper.

4.2 Baseline Methods

We implemented several baseline methods by adapting random forests (RF) and naïve Bayes classifier (NB), as well as class association rules (CAR) [24] and collaborative filtering based on singular value decomposition (SVD) [31]. Below we provide a brief sketch of these methods, focusing on how to produce training data using the co-occurring edge sets W.

To produce the training data for classification methods RF and NB, each co-occurring edge set $w \in W$ with t positive edges and t' negative edges was converted to t training examples, with a different positive edge as the class label of each training example containing $t-1+t'$ attributes. For instance, w_1 in Table 1 was converted to $\langle(\textit{education}, \overline{\textit{nationality}}), (\textit{founder})\rangle$ and $\langle(\textit{founder}, \overline{\textit{nationality}}), (\textit{education})\rangle$, where *founder* is the class of the first training example and *education* the class for the second training example. Multi-class classification models were learnt for RF and NB, wherein the number of classes equals the number of distinct positive edge types found in W.

For CAR, we generated multiple rules from W. For a co-occurring edge set with t positive edges and t' negative edges, we generated t association rules. The antecedent (left hand side) of each rule contains $t-1+t'$ attributes, while the consequent (right hand side) contains exactly one positive edge. For instance, w_1 in Table 1 was converted to rules $\langle \textit{education}, \overline{\textit{nationality}} \rightarrow \textit{founder}\rangle$ and $\langle \textit{founder}, \overline{\textit{nationality}} \rightarrow \textit{education}\rangle$. The strength of a rule was measured by the commonly used support and confidence [2] in association rule mining. If the antecedent of a rule and the ongoing session Q overlap, the rule's consequent as a suggestion to the user is weighted by the degree of overlap. For each candidate edge (i.e., consequent), its score is aggregated over related rules' strengths, modified by the above-mentioned weights.

For SVD, we generated a $|W|$ rows $\times$ $|T|$ columns sparse matrix from W. Each element in the matrix was assigned a value of 0 or 1, based on the occurrence of the edge (column) in the co-occurring edge set (row). For example, for W in Table 1, in the first row of the matrix, the columns corresponding to *education*, *founder* and $\overline{\textit{nationality}}$ were set to 1, while the rest were set to 0.

4.3 Random Decision Paths (RDP)

Here we describe random decision paths (RDP), a novel method for measuring the relevance of candidate edges. The RDP formulation is motivated by random forests [12]. However, RDP has important differences from the standard definition and application of random forests. It takes into account the idiosyncrasies of our problem and substantially outperforms standard random forests in experiments.

4.3.1 Motivation: from Random Forests to Random Decision Paths

To better understand the similarities and differences between RDP and random forests, it is useful to briefly review decision trees and random forests. In a general classification setting, a decision tree D defines a probability function $P_D(y|x)$, where x is a pattern, and y is the class of that pattern. The decision tree D can also be seen as a function that maps patterns to classes: $D(x) = \arg\max_y P_D(y|x)$. The output of tree D on a pattern x is computed by applying to x a test defined at the root of D, and using the result of the test to direct x to one of the children of the root. Each child of the root is a decision tree in itself, and thus x moves recursively along a path from the root to a leaf, based on results of tests applied at each node. A leaf node L stores precomputed probabilities $P_L(y)$ for each class y. If pattern x ends up on a leaf L of D, then the tree outputs $P_D(y|x) = P_L(y)$.

A random forest F is a set of decision trees. A forest F defines a probability $P_F(y|x)$, as the average $P_D(y|x)$ over all trees $D \in F$. To construct a random forest, each tree is built by choosing a random feature to test at each node, until reaching a predetermined number of trees. The probability values stored at the leaves of each tree are computed using a set of training patterns, for each of which the true class is known.

Random forests can be applied to our problem, but have certain undesirable properties. The input pattern x is a query session Q (cf. Definition 5). The training patterns are co-occurring edge sets in W (cf. Section 4.1). Each input and training pattern typically contains from a few to a few tens of positive and negative edges. The total number of edge types can reach thousands (it equals 5253 in one of our experiment datasets). The test applied at each node of a decision tree simply checks if a certain edge (positive or negative) is present in the pattern. Consider a training example, i.e., a co-occurring edge set $w \in W$, received by a path ending at leaf node L. Any positive edge y in w that is not tested along the path contributes to $P_L(y)$. Since patterns contain relatively few edges compared to the number of edge types, for most tests the vast majority of results is a "no", meaning that the pattern does not contain the edge specified in the test. This leads to highly unbalanced trees, where the path corresponding to all "no" results gets the majority of training examples, and paths corresponding to more than 1-2 "yes" results frequently receive no training examples. At classification time, the input pattern x ends up at the all-no path most of the times, and thus the class probabilities $P_D(y|x)$ do not vary much from the priors $P(y)$ averaged over all training examples.

Our solution to this problem is mathematically equivalent to constructing a random forest on the fly, given a query session Q to classify. This random forest is explicitly constructed to classify Q, and is discarded afterwards; a new forest is built for every Q. The tests that we use for tree nodes in that forest consider exclusively edges that appear in Q. This way, the probabilities stored at leaf nodes are computed from training examples that are similar to Q in a sense, as they share at least some edges with Q. This is why we expect these probabilities to be more accurate compared to the probabilities obtained from a random forest constructed offline, without knowledge of Q. This expectation is validated in the experiment results.

Since a different on-the-fly random forest is explicitly constructed for each Q, constructing full random forests is not necessary, and we can save significant computational time by exploiting this fact. The key idea is that, for any decision tree D that we may build, since we know Q, we know the path that Q is going to take within that tree. Computing the output for any other paths of D is useless, since D is constructed for the sole purpose of being applied to Q. Therefore, out of every tree in the random forest, we only need to compute and store a single path. Consequently, our random forest is reduced to a set of decision paths, and this set is what we call "random decision paths" (RDP). The ensuing discussion explains the idea in further detail.

4.3.2 Formulation of Random Decision Paths

Given query session Q and co-occurring edge sets W, our method RDP builds a set $\mathcal{R}$ of N random decision paths, i.e., $|\mathcal{R}| = N$, where N is a given size parameter. The random decision paths are specific to Q in that each $R \in \mathcal{R}$ contains a different random subset of the positive/negative edges in Q. I.e., $R \subseteq Q$ and $\mathcal{R} \subset \mathcal{P}(Q)$, in which $\mathcal{P}(Q)$ denotes the power set of Q. We want $\mathcal{R}$ to be much smaller than $\mathcal{P}(Q)$, i.e., $|\mathcal{R}| \ll |\mathcal{P}(Q)|$. In other words, we consider a virtual space of all possible decision paths, but only instantiate and use a few.

For each chosen random decision path R, we estimate the relevance of a edge e to R by the following scoring function. It measures, if the edges in R co-occur in a query session, how likely e should also appear in it. This is similar to the measure of confidence in association rule mining. Note that the scores of different edges do not form a probability distribution, since their summation can be larger than 1. This is because the same co-occurring edge set w may contribute to the scores of multiple edges. This is a deviation from the conventional decision tree in which each leaf node L stores precomputed probabilities $P_L(y)$ for each class y.

$$\text{score}_R(e) = \frac{|\{w|w \in W,\, R \cup \{e\} \subseteq w\}|}{|\{w|w \in W,\, R \subseteq w\}|} \tag{2}$$

The final score of a candidate edge $e \in C$ for query session Q is given by

$$\text{score}_Q(e) = \frac{1}{|\mathcal{R}|} \times \sum_{R \in \mathcal{R}} \text{score}_R(e) \tag{3}$$

In choosing random decision path R to be included into $\mathcal{R}$, we want each chosen path to be sufficiently specific and selective. It means that we expect such a chosen path to be satisfied by a sufficiently small number of training examples, i.e., it has a relatively small *coverage*. If R is satisfied by many training examples, their class labels may be quite diverse and R may not be discriminating enough. On the other hand, we also expect the path's coverage to be sufficiently large. If the coverage is too small, we run into overfitting and can be susceptible to noisy training examples. The measure *coverage* of a random decision path is defined as

$$\text{coverage}(R) = |W_R|, \text{where } W_R = \{w|w \in W, R \subseteq w\} \tag{4}$$

The space of possible random decision paths can become very large for a long query session, as $|\mathcal{P}(Q)| = 2^{|Q|}$. For this reason, RDP does not exhaustively enumerate all such paths and calculate their coverage. Instead, RDP grows each random decision path by sequentially adding edges from Q into the path. When the path gets longer, its coverage monotonically decreases. RDP continues to grow the path as long as its coverage is above a threshold τ, indicating the path is not sufficiently selective yet. The growing of the path immediately stops when its coverage falls below τ, because a more selective path may be susceptible to noises, as mentioned above. It also stops when all edges in Q are exhausted. In such a case, the path is not included.

Figure 3 shows an illustration of using random decision paths to rank the candidate edges. The candidate edges are C = {*writer*, *producer*, *editor*} and the query session Q contains edges *starring*, *education*, *director*, *nationality*, and *music*. $path_1$ through $path_N$ are examples of various random decision paths. For instance, decision path $path_2$ consists of edges *director* and *nationality*, which lead to W_2 where $|W_2| \leq \tau$.

Algorithm 1 displays the pseudo code of the random decision paths based edge ranking algorithm. Given a set of candidate edges C and a query session Q, RDP instantiates N random decision paths (line 2). Each path R is constructed by iteratively adding edges from Q. At every iteration, the next edge of the path is chosen uniformly at random without replacement (line 6). After a new edge is chosen, the coverage of the path $|W_R|$ is updated based on the definition in Equation 4 (line 10). A decision path R is grown until its coverage falls below the threshold τ (or there are no more edges to be chosen, whichever comes cost). The score of each candidate edge $e \in C$ is computed for each decision path (line 12). After all decision paths are chosen, the candidate edges are ranked by their final scores obtained using Equation 3 (line 17).

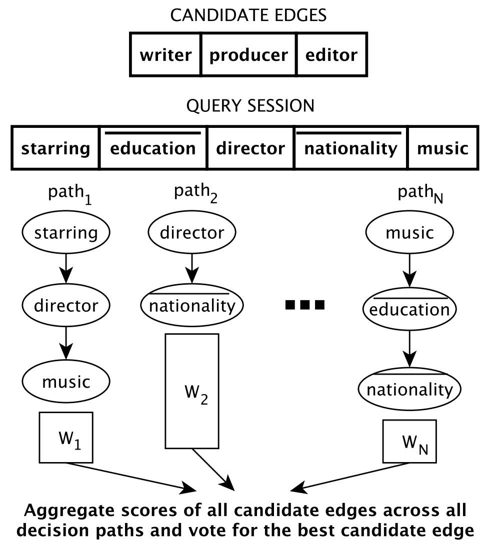


Figure 3: Random Decision Paths Based Edge Selection

5. GENERATING CO-OCCURRING EDGE SETS

For ranking candidate edges, RDP and all the baseline methods draw evidence from a collection of co-occurring edge sets W. In this section, we discuss several approaches to obtaining W, from the data graph itself, textual sources such as Wikipedia, and user query logs. Regardless of where W comes from, the commonality of the above-mentioned sources is that they provide insights on which edges (or corresponding relationships) are used together in forming queries (or writing articles) or possessed together by entities. Such co-occurrence information gives evidence useful to rank candidate edges by their relevance to the user's query intent. We use these different approaches to generate co-occurring positive edges in W. Then negative edges, which represent edge suggestions that are not accepted by users, are injected into W based on the positive edges.

Positive edges using Wikipedia and data graph (WikiPos)**:** Each Wikipedia article describes an entity in detail and refers to other Wikipedia entities by wikilinks. Given a sentence in a Wikipedia article (or a window of consecutive sentences), the multiple entities mentioned in it can be considered related in some way. We discover the pairwise relationships between these entities. Our premise is that these co-occurring relationships simulate the positive edges of a query session. The intuition is that such consecutive sentences may describe closely related facts, and an Orion user may also have such closely related facts as their query intent.

To find co-occurring positive edges, we map entities mentioned in Wikipedia articles to nodes in the data graph. Data graphs such as Freebase and DBpedia provide a straight-forward mapping of their nodes to Wikipedia entities. Given a sentence window, all edges found in the data graph between the mapped entities are approximated to the co-occurring positive edges of a co-occurring edge set in W. We consider all edges between the mapped entities in the data graph, while only a subset of these might actually be mentioned in the corresponding Wikipedia article. Thus, the co-occurring positive edges identified using this method might be noisy. We filter out co-occurring positive edges with less support. Every co-occurring edge set in W is viewed as an itemset. We use the Apriori algorithm [2] to generate frequent itemsets, subject to a

Algorithm 1: Random Decision Paths Based Edge Suggestion

Input: Data graph G_d, co-occurring edge sets W, candidate edges C, query session Q, number of random decision paths N, coverage threshold τ

Output: Ranked list of candidate edges

$\mathcal{R} \leftarrow \phi$;
while $|\mathcal{R}| < N$ **do**
    $R \leftarrow \phi$;
    $W_R \leftarrow W$;
    while $|R| < |Q|$ **do**
        $e_{rand} \leftarrow$ *sample_without_replacement*(Q);
        $R \leftarrow R \cup \{e_{rand}\}$;
        foreach $w \in W_R$ **do**
            if $e_{rand} \notin w$ **then**
                $W_R \leftarrow W_R \setminus \{w\}$;
        if $|W_R| \leq \tau$ **then**
            foreach $e \in C$ **do**
                $\mathrm{score}_R(e) \leftarrow$ Equation 2;
            $\mathcal{R} \leftarrow \mathcal{R} \cup \{R\}$;
            break;
foreach $e \in C$ **do**
    $\mathrm{score}_Q(e) \leftarrow$ Equation 3;
/* Return candidate edges by decreasing order of $\mathrm{score}_Q(.)$;*/

support ρ_w. The resulting frequent itemsets thus form co-occurring edge sets with only positive edges.

Positive edges using the data graph (DataPos): Another way of finding co-occurring positive edges is to use statistics based on the data graph G_d alone. For every node $v \in V(G_d)$, an itemset is created which includes all edges incident on v in G_d. This way we converted the graph G_d to $|V(G_d)|$ itemsets. Here too, we apply the Apriori algorithm to find all frequent itemsets using support ρ_d.

Positive edges using SPARQL query log (SparqlPos): To the best of our knowledge, existing visual query builders do not release publicly available query logs from their usage. The DBpedia SPARQL query benchmark [25] records queries posed by real users through the SPARQL query interface to DBpedia. Although it is not the query log of a visual query builder and it is applicable only for the DBpedia data graph, we use it to simulate the positive edges used in query sessions. More specifically, we extracted co-occurring positive edges using the properties specified in the WHERE clauses of the queries in this benchmark. Every set of positive edges found in each WHERE clause is used as is, without applying any pruning as in WikiPos and DataPos. One limitation of this benchmark is that only a third of the edge types in DBpedia are present in it.

Injecting negative edges (InjectNeg): The aforementioned methods only generate co-occurring edge sets W with positive edges. But it is crucial to simulate negative edges as well, since we must rank candidate edges that are correlated with both accepted and ignored edges in a query session. A simple, but effective strategy is used to introduce negative edges into W. For a co-occurring edge set $w \in W$, $T(w)$ is the set of node types of end nodes of all edges in w. I.e., $T(w) = \{t | t \in T_V, \exists e{=}(u,v) \in E(G_d), \mathrm{etype}(e) \in w \text{ s.t. } t \in \mathrm{vtype}(u) \text{ or } t \in \mathrm{vtype}(v)\}$. The set of negative edges added to w, denoted $\overline{w}$, is the set of all edges incident on the node types in $T(w)$, excluding the positive edges. I.e., $\overline{w} = \{\overline{\mathrm{etype}(e)} \mid e{=}(u,v) \in E(G_d), \mathrm{vtype}(u) \in T(w) \text{ or } \mathrm{vtype}(v) \in T(w), \mathrm{etype}(e) \notin w\}$. The new entry for every $w \in W$ consists of $w \cup \overline{w}$. The final entries in W are used by the various candidate edge ranking methods in Section 4.

W	**Components Used in Generating W**			
	Freebase	**DBpedia**	**Wikipedia**	**SPARQL** [25]
Wiki-FB	Yes	-	Yes	-
Data-FB	Yes	-	-	-
Wiki-DB	-	Yes	Yes	-
Data-DB	-	Yes	-	-
QLog-DB	-	-	-	Yes

Table 2: Co-occurring Edge Sets W Used in Experiments

Query Type	Query Task
Easy	Find all Basketball players in Chicago Bulls.
Medium	Find all award winning films directed by Steven Spielberg.
Hard	Find all film-actor pairs such that the actor was born in Israel and studied in Harvard University.

Table 3: Sample Query Tasks in User Studies

6. EXPERIMENTS

6.1 Setup

We conducted user studies on a double quad-core 24 GB memory 2.0 GHz Xeon server. Furthermore, RDP was compared with other edge ranking algorithms (RF, NB, CAR and SVD) on a Linux cluster which consists of five Dell PowerEdge R910 server nodes, with four Intel Xeon E7540 2.0GHz 6-core processors on each node, and a total of 1TB memory.

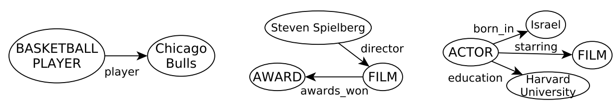
Datasets: We used two large real-world data graphs: the 2011 version of Freebase [10], and the 2015 version of DBpedia [4]. We pre-processed the graphs to keep only nodes that are named entities (e.g., Brad Pitt), while pruning out nodes corresponding to constant values such as integers and strings among others. In the original Freebase dataset, every relationship has a reverse relationship in the opposite direction. For instance, the relationship *director* has *directed by* in the opposite direction. We only keep one edge in each pair of reversed edges, since they are redundant. The resulting Freebase graph contains 30 million nodes, 33 million edges, and 5253 edge types. After similar pre-processing, the DBpedia graph obtained contains 4 million nodes, 12 million edges and 647 edge types.

Co-occurring Edge Sets W: Table 2 lists various co-occurring edge sets W produced using the techniques in Section 5. The approaches in Section 5 generate positive edges in W by different methods (WikiPos, DataPos, SparqlPos), and inject negative edges into them using the method InjectNeg. We generated two different Ws for Freebase: Wiki-FB and Data-FB. The positive edges in Wiki-FB were produced by WikiPos (using the September 2014 snapshot of Wikipedia and the Freebase data graph), and the positive edges in Data-DB were produced by DataPos (using only the Freebase data graph). We generated three different Ws for DBpedia: Wiki-DB, Data-DB and QLog-DB. Wiki-DB and Data-DB were produced via the same approach for Wiki-FB and Data-FB, except that DBpedia (instead of Freebase) was the data graph. For QLog-DB, the positive edges were produced by SparqlPos.

Systems Compared in User Studies: To verify if Orion indeed makes it easier for users to formulate query graphs, we conducted user studies with two different user interfaces: Orion, and Naive. Orion operates in both passive and active modes (cf. Section 3.2). Naive on the other hand does not make any automatic suggestions and only lets users manually add nodes and edges on the canvas.

Likert Scale Score	**Q1:** How well do you think the query graph formulated by you captures the required query intent?	**Q2:** How easy was it to use the interface for formulating this query?	**Q3:** How satisfactory was the overall experience?	**Q4:** The interface provided features necessary for easily formulating query graphs.
1	Very Poorly	Very Hard	Unacceptable	Strongly Disagree
2	Poorly	Hard	Poor	Disagree
3	Adequately	Neither Easy Nor Hard	Satisfactory	Uncertain
4	Well	Easy	Good	Agree
5	Very Well	Very Easy	Excellent	Strongly Agree

Table 4: Survey Questions and Options



(a) Easy (b) Medium (c) Hard

Figure 4: Target Query Graphs of Tasks in Table 3

System	**Queries**	**Sample Size**	**Conversion Rate** (c)	**z-value**	**p-value**
Orion	All	105	c_O=0.74	0.92	0.1788
Naive			c_N=0.68		
Orion	Medium + Hard	60	c_O=0.70	**1.36**	**0.0869**
Naive			c_N=0.58		

Table 5: Conversion Rates of Naive and Orion

The various candidate edges are sorted alphabetically and presented to the user in a drop down list. This mimics the query formulation support offered in existing visual query systems such as [17].

Methods Compared for Ranking Candidate Edges: We compared the effectiveness of Orion's candidate edge ranking algorithm (RDP) with the baseline methods described in Section 4.2, including RF, NB, CAR and SVD.

6.2 User Studies

User Study Set-up: We conducted an extensive user study with 30 graduate students in the authors' institution. The students neither had any expertise with graph query formulation, nor did they have exposure to the data graphs. None of these students were exposed to this research in any way other than participating in the user study. We conducted A/B testing using the two interfaces, Orion and Naive. The underlying data graph for both systems was Freebase, and were hosted online on the aforementioned Xeon server. We arbitrarily chose 15 students to work with Orion, and the other 15 students worked with Naive. The users of Orion were not exposed to Naive, and vice versa. We created a pool of 21 query tasks, which consisted of three levels of difficulty. 9 queries were *easy*, 6 queries were *medium* and 6 queries were *hard*. The target query graphs for each easy and medium query tasks had exactly one and two edges, respectively. The target query graphs for hard query tasks had at least three and at most 5 edges. Table 3 lists one sample query for each of the three categories. Figures 4(a), (b) and (c) depict the target query graphs for the query tasks listed in Table 3.

We created 15 different query sheets, where each consisted of 3 easy, 2 medium and 2 hard query tasks, chosen from the pool of 21 queries designed. Each Orion and Naive user was given a query sheet as the task set to complete which ensured that users of both systems worked on the same query tasks. Each user was given an initial 15-minute introduction by the moderators regarding the data graphs, graph query formulation, and the user interface. The users then spent 45 minutes working on their respective query sheets. The users were allowed to ask any clarification questions regarding the tasks during the user study. Each user was awarded a gift card worth $\$15.00$ for their participation in the user study. Since 15 users worked on 7 queries each, we obtained a total of 105 responses for both Orion and Naive.

Survey Form: The users were requested to fill an online survey form at the end of each query task, thus resulting in 105 different survey form responses for each user interface. The survey form had four questions: $Q1$, $Q2$, $Q3$ and $Q4$, as listed in Table 4. Each question had five options, specifying the level of agreement a user could have with the particular aspect of the interface measured by the question. We assign a score for every option in each question based on the Likert scale shown in Table 4. The least favourable experience with respect to each question is assigned a score of 1, and the most favoured experience is assigned a score of 5.

6.2.1 Efficiency Based on Conversion Rate

Measure: One of the popular metrics used to measure the effectiveness of the systems compared in A/B testing is conversion rate c, which is the percentage of tasks completed successfully by users. The conversion rate is defined over a set of Tasks as:

$$c = \frac{\sum_{\mathrm{task}\in\mathrm{Tasks}} \mathrm{sim}(G_u, G_t)}{|\mathrm{Tasks}|} \tag{5}$$

where task is a query task assigned to the user, G_u is the corresponding query graph constructed by the user, and G_t is the actual target query graph corresponding to task. The similarity measure $\mathrm{sim}(G_u, G_t)$ captures the notion of success, based on how similar G_u is to G_t. Since we designed the query tasks, the target query graph for each query task was known to us apriori. The query graph constructed by each user was recorded by the interface during the user study. Intuitively, the similarity between G_u and G_t is based on the edge-preserving sub-graph isomorphic match between the two graphs. More formally, $sim(G_u, G_t)$ is defined as:

$$\mathrm{sim}(G_u, G_t) = \frac{\max_f \sum_{\substack{e=(u,v)\in E(G_u)\\ e'=(f(u),f(v))\in E(G_t)}} \mathrm{match}(e, e')}{|E(G_t)|} \tag{6}$$

where $f : V(G_u) \to V(G_t)$ is a bijection, and $\mathrm{match}(e, e')$ is a matching function defined as:

$$\mathrm{match}(e, e') = \begin{cases} 1 & \text{if } u{=}f(u), v{=}f(v), etype(e) = etype(e') \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Results: Table 5 summarizes the conversion rates of Orion and Naive over the set of all query tasks (easy, medium and hard query tasks), and also over only the medium and hard query tasks. We observe that Orion has a better conversion rate than Naive in both scenarios. But, on performing a two sample Z-test with significance level α=0.1, only the observation that Orion has a better conversion rate than Naive for medium and hard queries is statistically significant. We next describe the hypothesis testing of the two scenarios in detail.

The conversion rate of Orion, c_O, over all the 105 query tasks is 0.74, and the conversion rate of Naive, c_N, for the same set of tasks is 0.68. On average, Orion users had a higher chance of formulating the correct query graph compared to the Naive users. We assume that constructing a query graph follows a Bernoulli trial, with the probability of successfully constructing the target query graph on Orion and Naive as $p_O = c_O$ and $p_N = c_N$ respectively. Our hypothesis, H_{A1}, is that Orion has a better conversion rate than Naive: H_{A1}: $p_O > p_N$. The null hypothesis H_{01} is given by H_{01}: $p_O \leq p_N$. For the aforementioned conversion rates of Orion and Naive, and a sample size of 105, $z = 0.92$. This results in a p-value of 0.1788. Since the p-value $> \alpha$, the null hypothesis cannot be rejected as the data does not significantly support our hypothesis.

We dive in deeper to investigate if there are scenarios where Orion does perform better than Naive. The conversion rate of only medium and hard query tasks (which is equal to a total of 60 query tasks) for Orion is 0.70, and is equal to 0.58 for Naive, i.e., $c_O = p_O = 0.70$ and $c_N = p_N = 0.58$. This indicates that Orion users have a better chance of successfully constructing query graphs with two or more edges, compared to Naive users. Our new hypothesis, H_{A2}, is that Orion has a better conversion rate than Naive for medium and hard queries: H_{A2}: $p_O > p_N$. The null hypothesis H_{02} is given by H_{02}: $p_O \leq p_N$. For the aforementioned conversion rates of Orion and Naive, and a sample size of 60, $z = 1.36$, resulting in a p-value of 0.0869. Since the p-value $< \alpha$, the data significantly supports our claim that Orion users have a higher chance of successfully constructing complex query graphs containing two or more edges.

6.2.2 *Efficiency Based on Time*

We next measure the time taken by a user to construct the query graph for a given query task: the time elapsed between the first time a user clicks on the query canvas for a new query task, to the time the user clicks on the "Submit" button of the interface. This was recorded in the background during the user study. Figure 5(a) shows the distribution of the time taken to complete a query task. We observe that half of the 105 query tasks were completed within 180 seconds by Orion users, while Naive users completed the same number of query tasks within 183.2 seconds. Around 26 query tasks were completed between 180 to 340.5 seconds, and between 183.24 to 325.7 seconds by Orion and Naive users respectively. Although, there were a few query tasks that took a long time to be completed, with a maximum of 1446.3 seconds for Orion users and 1027.8 seconds for Naive users. We further study the distribution of the time taken to complete query tasks based on the level of difficulty of the tasks. Figure 5(b) compares the time taken for easy query tasks. We observe that around 23 of the 45 easy queries are completed within 135.5 and 130.3 seconds by Orion and Naive users respectively. Another 12 queries were completed between 135.5 to 202.3 seconds by Orion users, and between 130.3 to 211.3 seconds by Naive users. Figure 5(c) compares the time taken for medium query tasks. We observe that around 15 of the 30 medium queries are completed within 188.2 and 224.6 seconds by Orion and Naive users respectively. Another 7 queries were completed between 188.2 to 349.6 seconds by Orion users, and between 224.6 to 296.2 seconds by Naive users. Finally, Figure 5(d) compares the time taken for hard query tasks. We observe that around 15 of the 30 hard queries are completed within 296.1 and 259.6 seconds by Orion and Naive users respectively. Another 7 queries were completed between 296.1 to 540.4 seconds by Orion users, and between 259.6 to 406.4 seconds by Naive users. We observe that despite the steeper learning curve of Orion due to the superior number of features in it, the time taken to complete a majority of the query tasks is comparable with that of Naive.

6.2.3 *Efficiency Based on Number of Iterations*

We next measure the effectiveness of Orion using the number of iterations involved in the query construction process: the number of times a ranked list of edges is presented to the user. The number of iterations is incremented in one of three ways: 1) the user selects one or more of the automatically suggested edges in active mode, and clicks on the canvas to get the next set of suggestions, 2) the user ignores all the suggestions made in active mode and clicks on "Refresh Suggestions" to get a new set of automatic suggestions, and 3) the user draws a new edge in passive mode. We do not measure this for Naive since there are no automatic ranked suggestions made in it. Figure 6 shows the distribution of the number of iterations required to construct query graphs. Overall, Orion users needed no more than only 13 iterations to complete around 79 of the 105 queries. Half of the easy, medium and hard queries required no more than 3, 10 and 14 iterations respectively. Another 11 easy queries required between 3 to 7 iterations, while 7 medium and hard queries each required between 10 to 15.5 and 14 to 23.5 iterations respectively. This indicates that the features offered by Orion helped users formulate query graphs with few interactions with the interface.

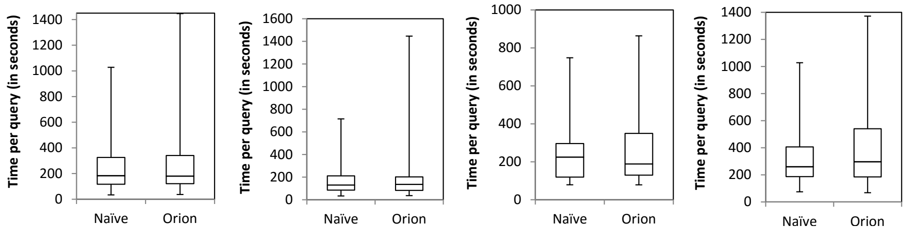
6.2.4 *User Experience Results*

The user experience results is based on the answers to all the questions in the survey form by all the users. The overall user experience for each question of an interface is measured by averaging the score obtained for that question across all the users working on that interface. Figure 7(a) shows the overall user response of all the questions, across all the 105 users for both Orion and Naive. We observe that Orion users report an improvement of 0.5 for $Q1$, 0.2 for $Q2$, 0.25 for $Q3$ and 0.3 for $Q4$ on Likert scale, when compared to the Naive users.

We further break down the average score over each question based on the difficulty level of the query task to study the difference in user experience between Orion and Naive in detail. Figure 7(b) shows the average score over only the easy query tasks (a total of 45 query tasks each for both Orion and Naive), which shows that Orion users had a better experience than the Naive users w.r.t $Q1$, while the Naive users had a slightly better experience than Orion users w.r.t $Q2$ and $Q3$. Both the sets of users had similar experience w.r.t $Q4$. Figure 7(c) shows the average score over only the medium query tasks (a total of 30 query tasks each for both Orion and Naive), which shows that Orion users had an improvement of 0.4 on Likert scale w.r.t $Q1$ and $Q4$ compared to the Naive users. They also had an improvement close to 0.1 on Likert scale w.r.t both $Q2$ and $Q3$. Finally, Figure 7(d) shows the average score over only the hard query tasks (a total of 30 query tasks each for both Orion and Naive), which shows that Orion users felt a significant improvement in the user experience across all four questions. Orion users had an improvement of around 1.0 w.r.t $Q1$, 0.6 w.r.t $Q2$, and 0.7 w.r.t both $Q3$ and $Q4$. We thus observe that as the difficulty level of the query graph being constructed increases, the usability of Orion seems significantly better than Naive's. Naive users find the system uncomfortable to use when the target query graph contains two or more edges.

6.3 Comparing Candidate Edge Ranking Methods

We next compare the performance of RDP, Orion's edge ranking algorithm, with other data mining algorithms: RF, NB, SVD and



(a) All queries (b) Easy queries (c) Medium queries (d) Hard queries

Figure 5: User Studies Efficiency Based on Time: Naive **and** Orion

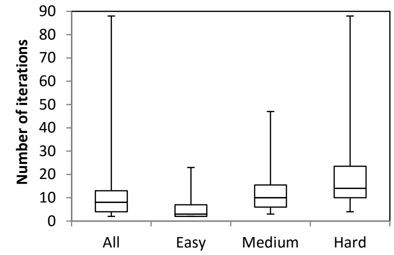
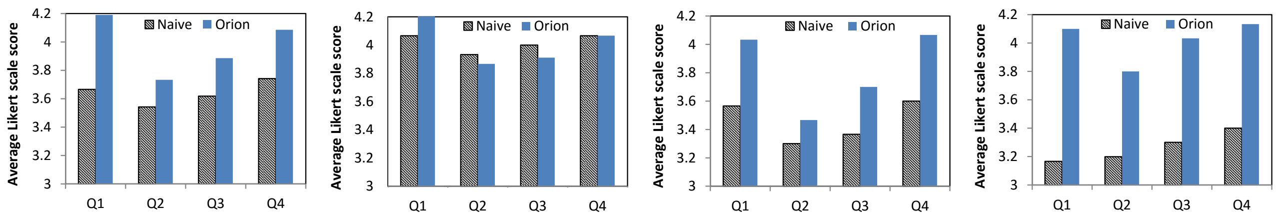


Figure 6: User Studies Efficiency Based on Iterations: Orion



(a) All queries (b) Easy queries (c) Medium queries (d) Hard queries

Figure 7: User Experience Based on Survey Responses

CAR. We compared the performance of these algorithms over two widely used real-world data graphs: Freebase and DBpedia. We used Wiki-FB and Wiki-DB as the co-occurring edge sets for Freebase and DBpedia, respectively. We had to perform these experiments on the aforementioned cluster, because RF has high memory requirements. For instance, generating a random forest model with 80 trees, using around 100,000 co-occurring edge sets, requires 55 GB of RAM.

We created multiple target query graphs for each dataset, conforming with the schema of the underlying data graph. For a given target query graph, the input to each of the algorithms was an initial partial query graph containing exactly one edge in it. The task of each algorithm was to iteratively suggest exactly one edge at a time, given the partial query graph. If the edge suggested was present in the target query graph, it was added into the partial query graph, and recorded as a positive edge. If not, the edge was ignored, and recorded as a negative edge. The process was stopped either when the partial query graph was grown completely into the target query graph, or if 200 suggestions were up. For each target query graph G_t containing $E(G_t)$ number of edges, we internally converted it into $E(G_t)$ different instances of target query graphs, each starting with a different-edged initial partial query graph as input to the algorithms.

We created 43 target query graphs for Freebase, consisting of 6 two-edged query graphs, 10 three-edged query graphs, 9 four-edged query graphs, 17 five-edged query graphs and 1 six-edged query graph. These 43 target query graphs were thus converted to 167 different input instances, creating a query set called *Freebase-Queries*. We created 33 target query graphs for DBpedia, consisting of 2 three-edged query graphs, 29 four-edged query graphs, and 2 five-edged query graphs. These 33 target query graphs were converted to 130 different input instances, creating a query set called *DBpedia-Queries*.

6.3.1 Efficiency Based on Number of Suggestions

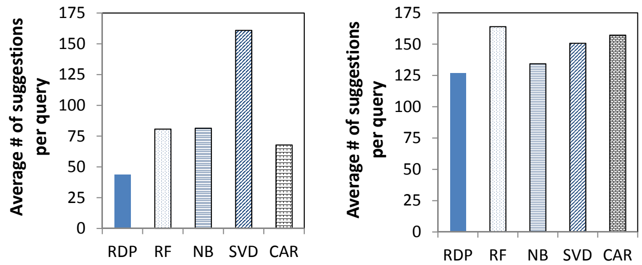
For a query graph completion system, we believe an important measure of its efficiency is the number of suggestions required to successfully grow a partial query graph to its corresponding target query graph. This is because, if a system can help users construct the target query graph with fewer number of suggestions, it indicates that the suggestions made indeed captured the user's query intent. Figure 8(a) shows the average number of suggestions required to complete each of the 167 input instances for Freebase. We observe that RDP significantly outperforms the other methods. RDP requires only 43.5 suggestions per query graph on average, nearly half the number of suggestions required to complete a query graph using RF and NB. It also requires only a quarter of the number of suggestions required to complete a query graph using SVD, while CAR requires 67.8 suggestions. Figure 8(b) shows the average number of suggestions required to complete each of the 167 input instances for DBpedia. We observe that RDP requires 126.6 suggestions on average to complete a query graph, performing slightly better than NB which requires 134.3 suggestions. RDP also comfortably outperforms RF, SVD and CAR which on average require 164, 150.7 and 157.9 suggestions per query graph respectively.

6.3.2 Efficiency Based on Time

We next compare the efficiency of the various methods over the time required to grow the initial partial query graph to its corresponding target query graph. Figure 9(a) compares the average time required to complete a query task by each of the algorithms over Freebase. RDP, NB and RF significantly outperform SVD and CAR. RDP requires 7.7 seconds, slightly higher than NB's 3.9 seconds, and better than RF's 11.8 seconds per query, which is commendable especially since both random forest and Bayesian classifiers are extremely efficient once the models are learnt. Figure 9(b) compares the average time required to complete a query task by each of the algorithms over DBpedia. SVD and CAR are inefficient requiring 250.2 and 444.2 seconds per query respectively. NB requires 5.9 seconds, which is faster than both RF and RDP that require 26.7 and 119.7 seconds per query respectively.

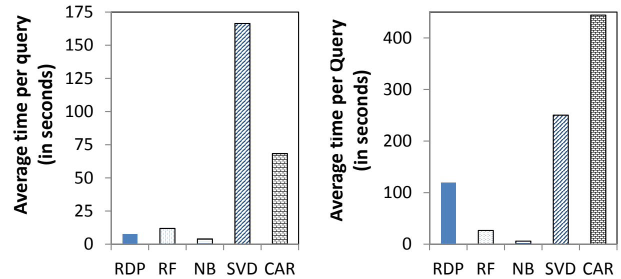
6.4 Effectiveness of Co-occurring Edge Sets W

We compared the effectiveness of the various co-occurring edge sets W listed in Table 2. We used RDP as the algorithm for edge suggestion, and the number of suggestions required to grow the initial partial query graph to the target query as the measure of effectiveness of W. Freebase-Queries and DBpedia-Queries,



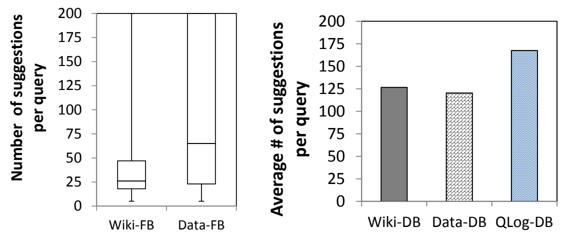
(a) Freebase (b) DBpedia

Figure 8: Efficiency of All Methods: Number of Suggestions



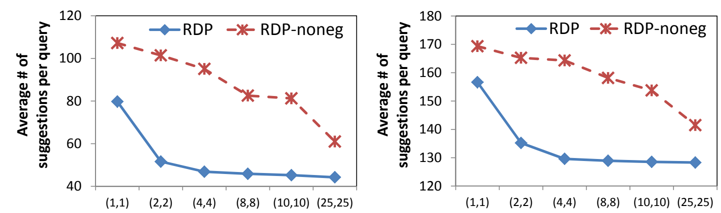
(a) Freebase (b) DBpedia

Figure 9: Efficiency of All Methods: Time



(a) Freebase (b) DBpedia

Figure 10: Effectiveness of Co-occurring Edge Sets



(a) Freebase (b) DBpedia

Figure 11: Effect of Parameters on RDP (N, τ)

described in Section 6.3, were the sets of queries used to compare the various W for Freebase and DBpedia.

W **for Freebase:** Figure 10(a) shows the distribution of the number of suggestions required to complete a query task using Wiki-FB and Data-FB as W, respectively. We observed that 83 of the 167 input instances needed no more than 26 edge suggestions with Wiki-FB, while it required at most 65 edge suggestions to complete the same number of queries using Data-FB. Around 42 more input instances required between 26 to 47 suggestions with Wiki-FB, while it required between 65 to 200 suggestions with Data-FB. This indicates that the W generated using Wikipedia and the Freebase data graph by WikiPos described in Section 5 is of superior quality compared to the one generated using only the Freebase data graph. This suggests that positive edges established based on the context of human usage of the relationships is better than the positive edges established using only the data graph.

W **for DBpedia:** Figure 10(b) shows the average number of edge suggestions required to process the 130 different DBpedia input instances, using each of the three aforementioned Ws for DBpedia. We first observed that QLog-DB performed poorly compared to the other two co-occurring edge sets. This is because the DBpedia SPARQL query log is not comprehensive enough and is limited in the variety of relationships captured, making it ineffective. The second observation is that the algorithm required 120.3 suggestions on average using Data-DB, while it required 126.6 suggestions with Wiki-DB. Data-DB performed slightly better than Wiki-DB due to the fact that DBpedia is a high-quality data graph generated using the info-boxes in Wikipedia pages. The sets of positive edges in Wiki-DB were simulated using the text in Wikipedia and the DBpedia data graph. The performance of Wiki-FB and Data-FB was thus highly similar, unlike the case in Freebase where we could see a significant difference.

6.5 Parameter Tuning for RDP

We studied a variation of RDP and the effect of N and τ, the two parameters used in RDP. As described in Section 4.3.2, given a query session Q, RDP builds N different random decision paths. Each random decision path is grown incrementally, until either the support for the path is no more than a threshold τ, or if all edges in Q are exhausted. While building a random decision path, RDP considers both the positive and negative edges. To study if considering the negative edges indeed helps in better identifying the user's query intent, we created a variation of RDP, called RDP-noneg, which does not include any negative edges in the random decision paths. Figures 11(a) and 11(b) compare the average number of suggestions required to complete each query graph with different values of N and τ, for Freebase and DBpedia queries, respectively. In both cases, we observed that the average number of suggestions required per query decreased as we increased the number of random decision paths and the threshold τ. It saturated after both N and τ reach around 10. Figures 11(a) and 11(b) also compare the average number of suggestions required to complete the query graphs using RDP and RDP-noneg. With the best parameter values of $N = 25$ and $\tau = 25$, RDP requires 44.2 suggestions while RDP-noneg requires 60.9 suggestions in Freebase. RDP also requires fewer suggestions in DBpedia with 128.5 suggestions compared to 141.5 suggestions required by RDP-noneg. We observed that RDP significantly outperformed its variant RDP-noneg, indicating that considering negative edges in query sessions is indeed helpful.

7. CONCLUSIONS

We introduce Orion, a visual query builder that helps schema-agnostic users construct complex query graphs by automatically suggesting new edges to add to the query graph. Orion's edge ranking algorithm RDP, ranks candidate edges by how likely they will be of interest to the user, using co-occurring edge sets generated from several sources, including the data graph itself, external textual sources, and user query logs. User studies show that Orion has a 70% success rate of building complex query graphs, significantly better than a baseline system resembling existing visual query builders, that has a 58% success rate. We also compare RDP with several methods based on other data mining algorithms and observe that, on average, those other methods require 1.5-4 more suggestions to complete query graphs.

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