

# Tackling Usability Challenges in Querying Massive, Ultra-heterogeneous Graphs

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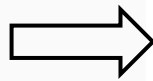


# Ultra-heterogeneous Entity Graphs

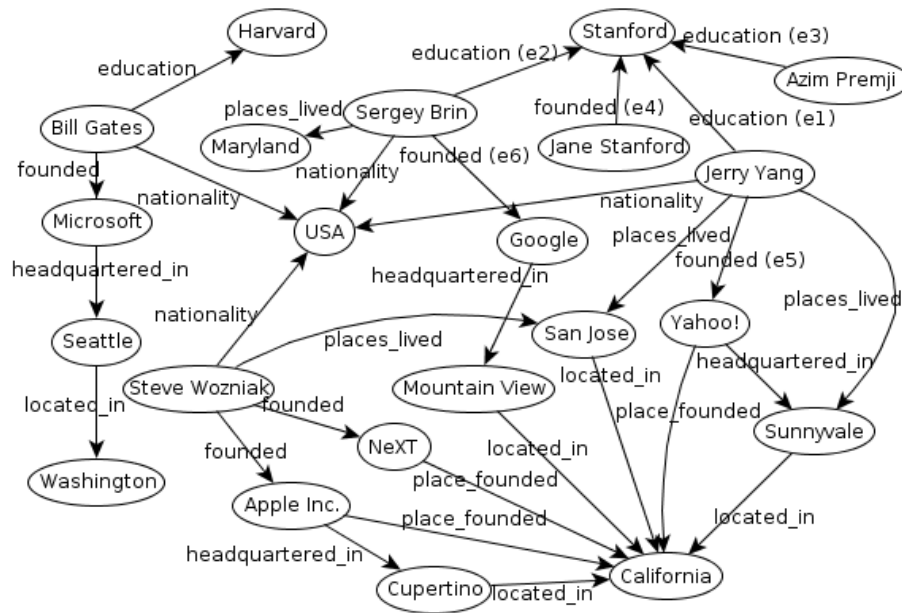
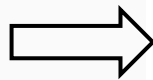


Large, complex and schema-less graphs capturing millions of entities and billions of relationships between entities.

entity



relationship



Linked Open Data : 52 billion RDF triples

Freebase : 1.8 billion triples

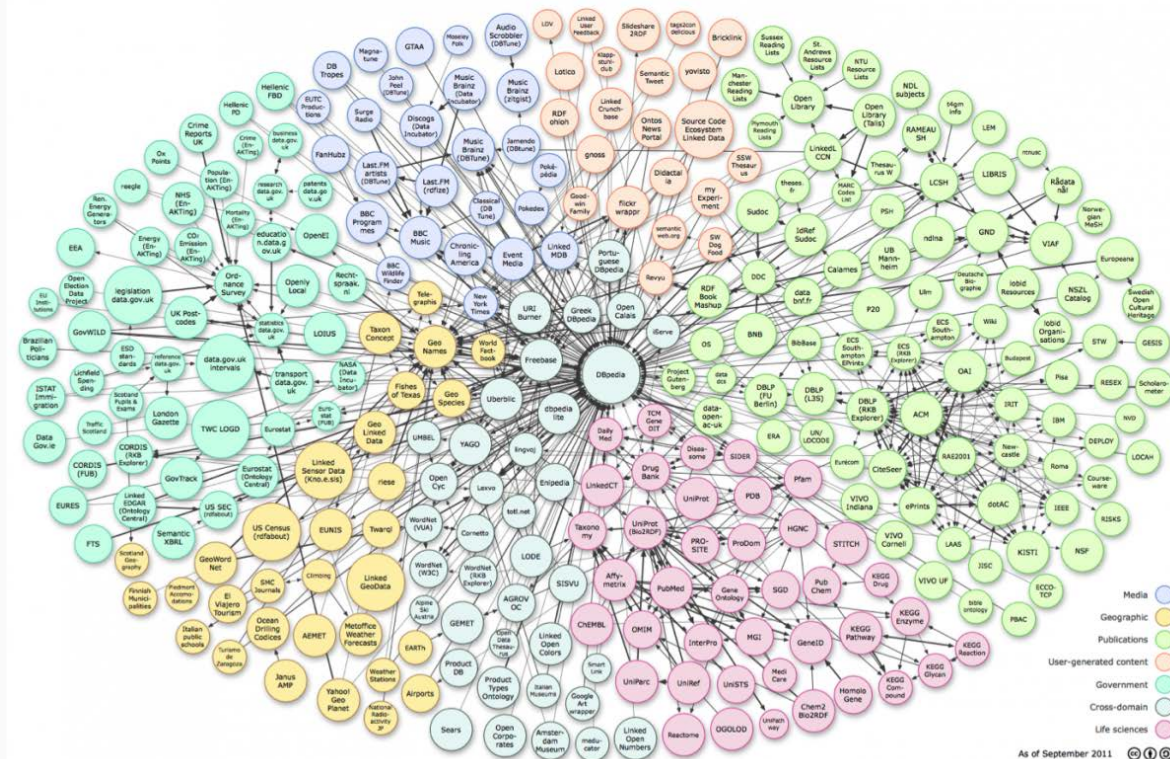
DBpedia : 470 million triples

Yago : 120 million triples

# Linked Open Data



<http://linkeddata.org/> (hundreds of datasets, billions of RDF triples)



# Structured Queries are Difficult to Write

## SQL QUERY:

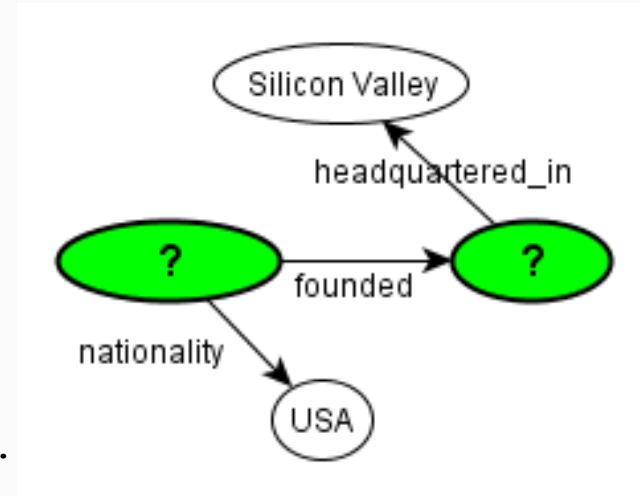
```
SELECT Founder.subj, Founder.obj
FROM Founder,
     Nationality,
     HeadquarteredIn
WHERE
     Founder.subj = Nationality.subj AND
     Founder.obj = HeadquarteredIn.subj
```

- Require knowledge on data model, query language, and schema.

- Well-known usability challenges [Jagadish+07]

## SPARQL QUERY:

```
SELECT ?company ?founder WHERE {
    ?founder dbo:founded ?company .
    ?founder dbo:nationality db:United_States .
    ?company dbprop:headquartered_in db:Silicon_Valley .
}
```





# Simpler Query Paradigms

## Keyword Search

- [Kargar+11], BLINKS [He+07]
  - Challenging to articulate exact query intent by keywords

## Approximate Query Answering

- NESS [Khan+11]: uses neighborhood-based indexes to quickly find approximate matches to a query graph;
- TALE [Tian+08]: approximate large graph matching
- Users still have to formulate the initial query graph

# Visual Query Builders



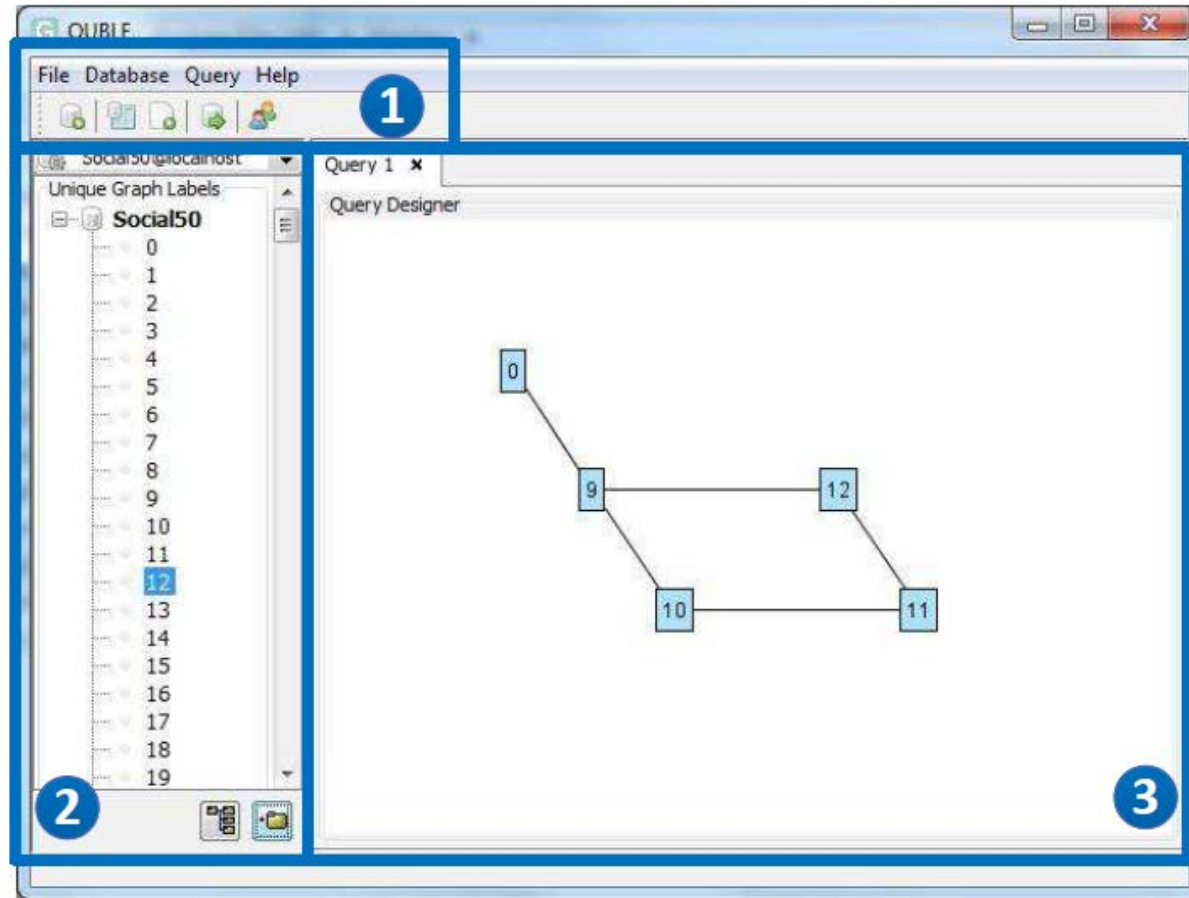
**Relational Databases:** CLIDE [Petropoulos+06]

**Graph Databases:** VOGUE [Bhowmick+13], PRAGUE [Jin+12], Gblender [Jin+10], GRAPHITE [Chau+08]

**Single Large Graphs:** QUBLE [Hung+13]

- Require a good knowledge of the underlying schema
- No automatic suggestions regarding what to include in the query graph

# An Example: QUBLE





# Orion: Auto-Suggestion Based Visual Interface for Interactive Query Construction



# Orion

Prototype

<http://idir.uta.edu/orion>



Introduction Video

<http://bit.ly/1O0GnNo>



# Objectives of Orion




- Interactive GUI for building query components
- Iteratively suggest edges based on their relevance to the user's query intent, according to the partial query graph so far

# Orion GUI

Dynamic list of all possible user actions at any given moment

Control panel for various settings and tips

  
orion

### Possible Actions

Click on other grey nodes to be included in the query graph.

Click on the grey edge to select it, or click on a grey edge to display the other occurrences of the grey edge, if any.

Click on the empty canvas to add the selected nodes and edges to the query graph while ignoring the unselected grey nodes, and display new suggestions.

Click on selected nodes (in blue) to unselect them.

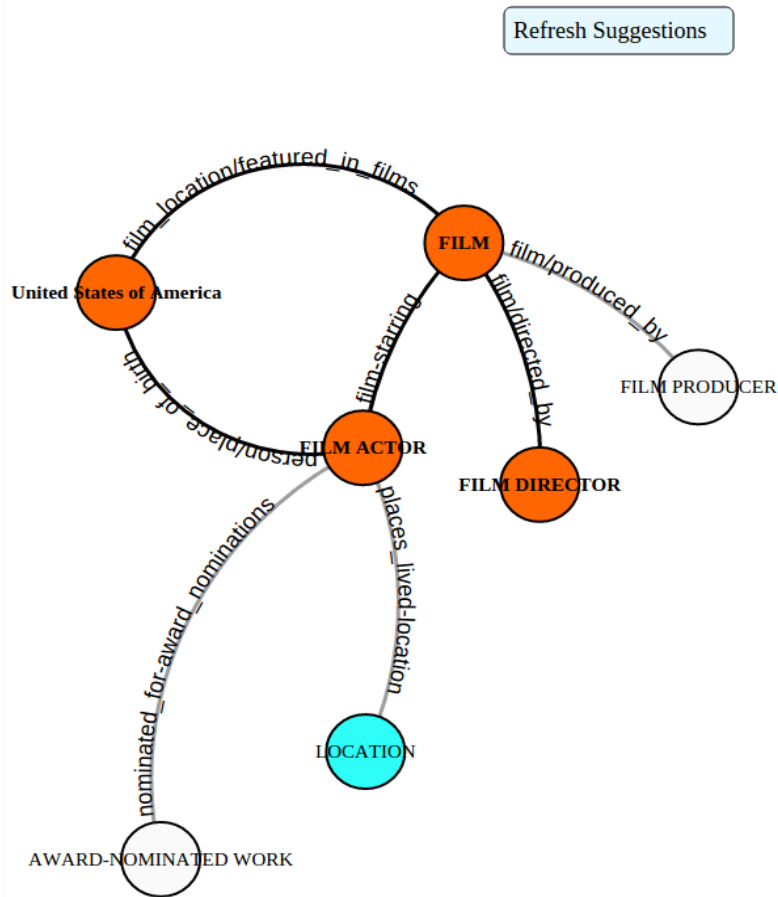
Submit

Useful Tips +

Edge Types +

Settings +

Clear Canvas

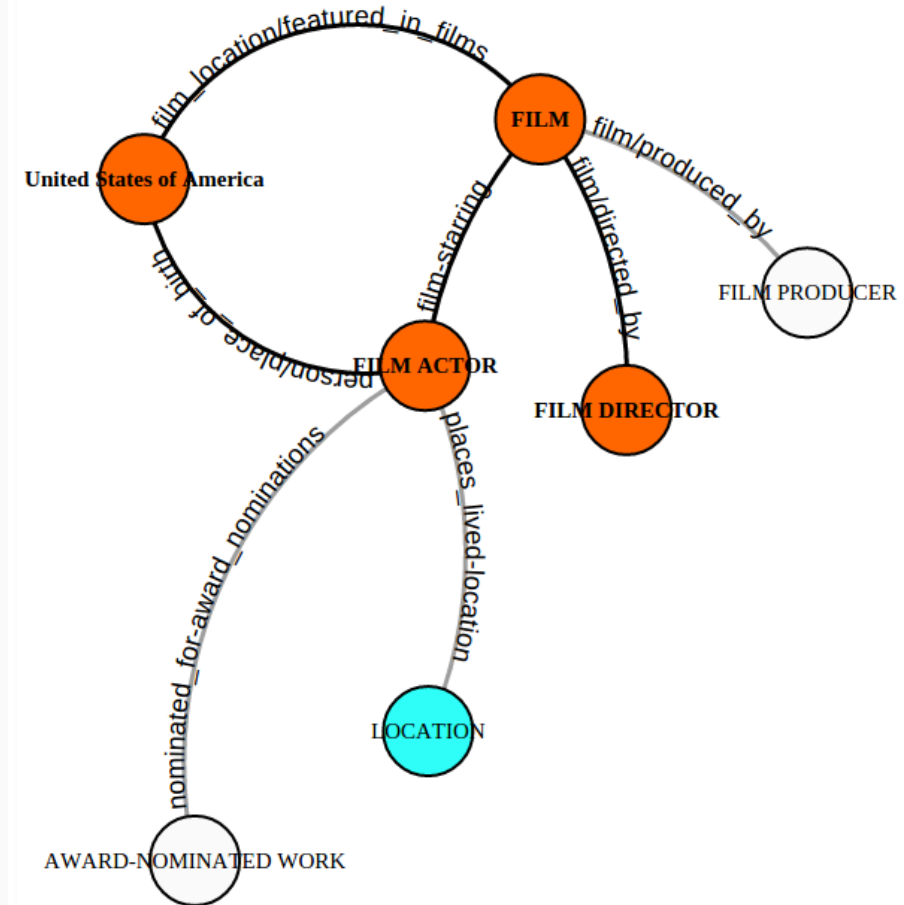


# Active Mode



Grey edges and nodes automatically suggested in **active mode**:

- Accepted by user (blue): **positive edges**
- Ignored by user: **negative edges**



# Passive Mode



Select Node Label

close

Domain: PEOPLE

Type: PERSON

Entity: Select Entity...

Select Help

A new node added in **passive mode**

A new edge added in **passive mode**

Select Edge Label

close

Edge Label: Select Edge

- Select Edge
- film-starring
- film/directed\_by
- writer/film
- film/produced\_by
- nominated\_for-award\_nominations
- honored\_for-awards\_won
- film/music
- film/story\_by
- editor/film
- personal\_appearances-person
- cinematographer/film
- producer/films\_executive\_produced
- surfing/surf\_film/surfers
- music\_video-music\_video\_performer
- film/film\_production\_design\_by
- dubbing\_performances-film
- film/film\_art\_direction\_by
- film/film\_casting\_director
- snl\_cast\_member-snl\_movie\_spin\_off

# Rank Candidate Edges for Suggestions



## Possible Solutions

- Order alphabetically
- Adapt standard machine learning algorithms
  - Naïve Bayes classifier
  - Random forests
  - Class association rules
  - Recommendation systems (based on SVD)

## Query-specific Random Decision Paths (RDP)

# Concepts



Edges in partial query graph (positive edges)

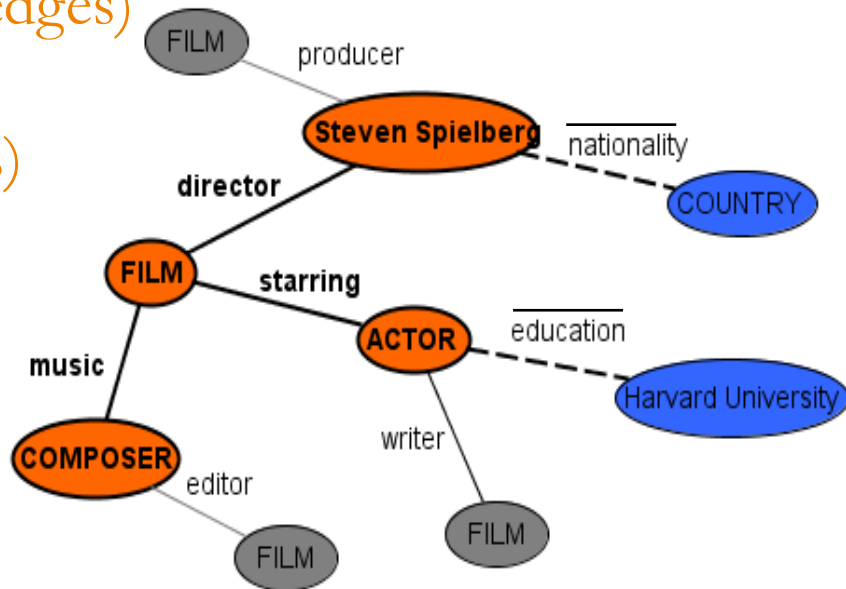
starring, director, music

Edges rejected by users (negative edges)

education, nationality

Candidate edges

producer, writer, editor



Query Session:

<starring, director, music, education, nationality>

# Concepts

## Query Log (W)



Positive Edge

Negative Edge

Id	Query Session
$w_1$	<u>education</u> , <u>founder</u> , <u>nationality</u>
$w_2$	<u>starring</u> , <u>music</u> , <u>director</u>
$w_3$	<u>nationality</u> , <u>education</u> , <u>music</u> , <u>starring</u>
$w_4$	<u>artist</u> , <u>title</u> , <u>writer</u> , <u>director</u>
$w_5$	<u>director</u> , <u>founder</u> , <u>producer</u>
$w_6$	<u>writer</u> , <u>editor</u> , <u>genre</u>
$w_7$	<u>award</u> , <u>movie</u> , <u>director</u> , <u>genre</u>
$w_8$	<u>education</u> , <u>founder</u> , <u>nationality</u>

## Problem

Given a query log, a query session, and a set of candidate edges, rank the candidate edges by their relevance to the user's query intent

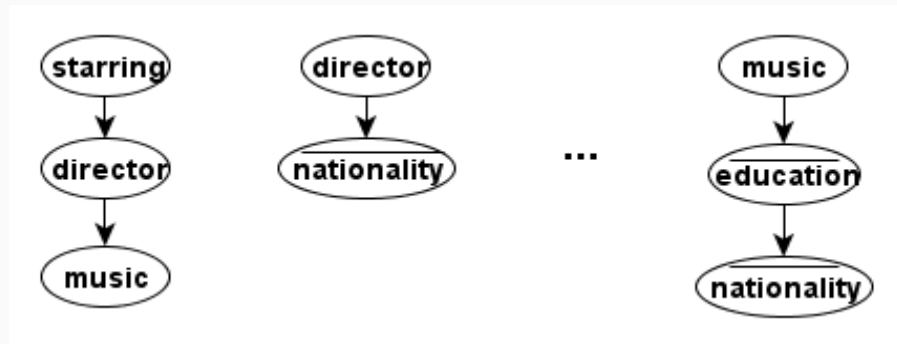


# Random Decision Path (RDP)



<starring, director, music, education, nationality>

- Choose edges from the query session randomly, to form RDPs



- Each decision path selects a subset of the query log, with no more than ' $\tau$ ' rows
- Grow a path incrementally until its support in the query log drops below ' $\tau$ '

# Random Decision Path: Scoring



- For each RDP, use its corresponding query log subset to compute the support of each candidate edge.
- Final score of each candidate is its average score across all RDPs.
- If  $R$  is the set of all RDPs:

$$score(e) = \frac{1}{|R|} * \sum_{Q_i \in R} sup(e, Q_i, W)$$

$$sup(e, Q_i, W) = \frac{|\{w \mid w \in W, Q_i \cup \{e\} \subseteq w\}|}{|\{w \mid w \in W, Q_i \subseteq w\}|}$$

# Query Log



Nonexistent (almost)

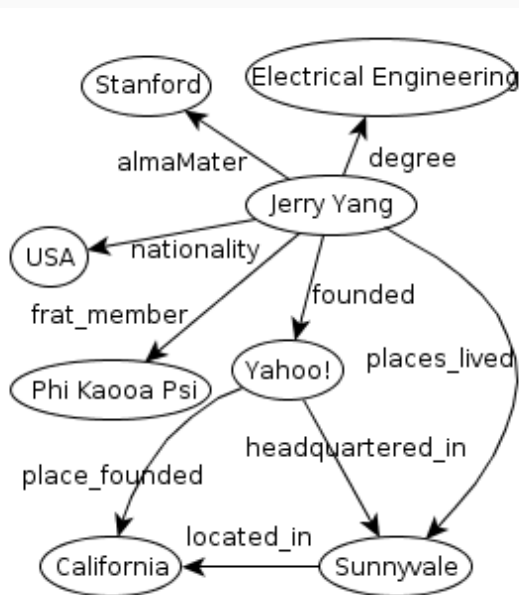
Simulate and bootstrap

- Find positive edges
  - Wikipedia and data graph
  - Data graph only
  - SPARQL query log [Morsey+11]
- Inject negative edges

Id	Query Session
$w_1$	<u>education</u> , <u>founder</u> , <u>nationality</u>
$w_2$	<u>starring</u> , <u>music</u> , <u>director</u>
$w_3$	<u>nationality</u> , <u>education</u> , <u>music</u> , <u>starring</u>
$w_4$	<u>artist</u> , <u>title</u> , <u>writer</u> , <u>director</u>
$w_5$	<u>director</u> , <u>founder</u> , <u>producer</u>
$w_6$	<u>writer</u> , <u>editor</u> , <u>genre</u>
$w_7$	<u>award</u> , <u>movie</u> , <u>director</u> , <u>genre</u>
$w_8$	<u>education</u> , <u>founder</u> , <u>nationality</u>

# Query Log Simulation: Wikipedia + Data Graph

## Use Sentences in Wikipedia Articles to Identify Positive Edges



### Early life [edit]

Yang was born in [Taipei, Taiwan](#) on November 6, 1968, and moved to [San Jose, California](#) at the age of ten with his mother and younger brother.<sup>[4]</sup> He claimed that despite his mother being an [English](#) teacher, he only knew one English word (shoe) on his arrival. Becoming fluent in the language in three years, he was then placed into an [Advanced Placement](#) English class.<sup>[5]</sup>

Yang graduated from [Sierramont Middle School](#) and [Piedmont Hills High School](#) in San Jose and went on to earn a [Bachelor of Science](#) and a [Master of Science](#) [electrical engineering](#) from [Stanford University](#) where he was a member of [Phi Kappa Psi](#) fraternity.<sup>[6][7]</sup>

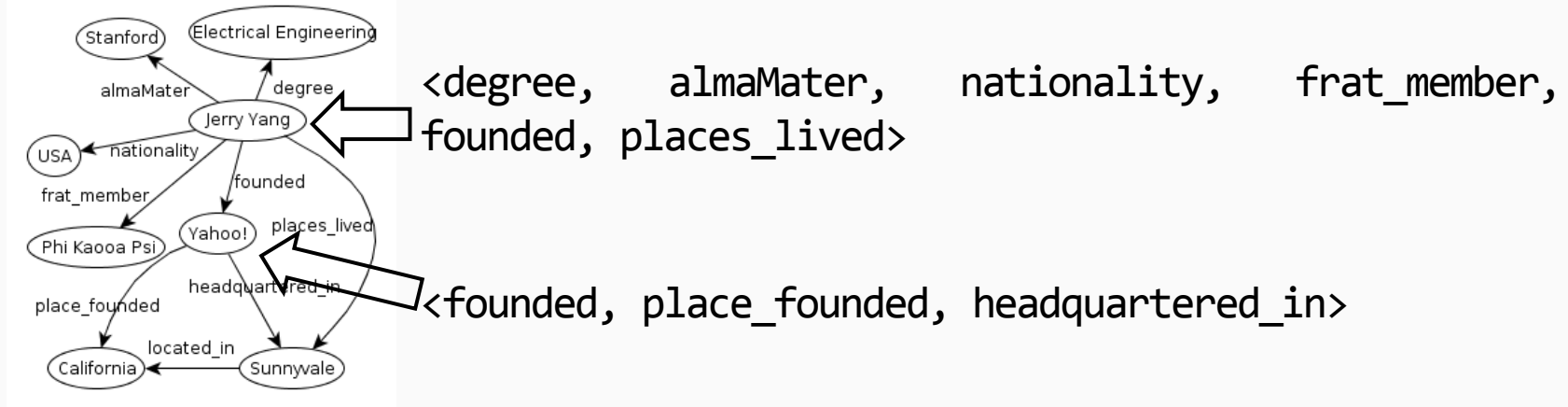
**Nodes Mapped:** Jerry Yang, Electrical Engineering,  
Stanford University, Phi Kappa Psi

<degree, almaMater, frat\_member>

# Query Log Simulation: Data Graph Only



Represent Each Node as an Itemset of Positive Edges



Generate Frequent Itemsets of Varying Sizes

- Each frequent itemset of edges forms positive edges

# Query Log Simulation: Injecting Negative Edges

## Positive Edges List

- (1) writer, starring, producer
- (2) starring, editor, education
- (3) editor, nationality, music

## Inject Negative Edges

writer, starring, producer, editor, education (starring appears in 2)

starring, editor, education, writer, producer, nationality, music (starring appears in 1, and editor appears in 3)

editor, nationality, music, starring, education (editor appears in 2)

## System Configurations

- Double quad-core 2.0 GHz Xeon server, 24 GB RAM
- TACC: 5 Dell PowerEdge R910 server nodes, with 4 Intel Xeon E7540 2.0 GHz 6-core processors, 1 TB RAM

## Datasets

- Freebase (33 M edges, 30 M nodes, 5253 edge types)
- DBpedia (12 M edges, 4 M nodes, 647 edge types)

# Experiments (cont.)



## User Studies

- Orion (RDP) and Naïve

## Edge Ranking Algorithms Compared

- Random Decision Paths (RDP)
- Naïve Bayes classifier (NB)
- Random forest classifier (RF)
- Class association rules (CAR)
- SVD based recommendation system (SVD)



# Query Logs Compared

- Freebase: Wiki, Data
- DBpedia: Wiki, Data, QLog

Query Log	Components Used in Query Log Simulation			
	Freebase	DBpedia	Wikipedia	SPARQL [26]
Wiki-FB	Yes	-	Yes	-
Data-FB	Yes	-	-	-
Wiki-DB	-	Yes	Yes	-
Data-DB	-	Yes	-	-
QLog-DB	-	-	-	Yes

# User Studies: Setup

15 Users for Orion, 15 Users for Naïve (A/B testing)

45 Easy, 30 Medium, and 30 Hard Query Tasks Designed

3 Easy, 2 Medium, 2 Hard Queries Assigned per Query Task

105 Query Tasks per System in Total

4 Survey Questions per Query Task

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 provide 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

# User Studies: Conversion Rate



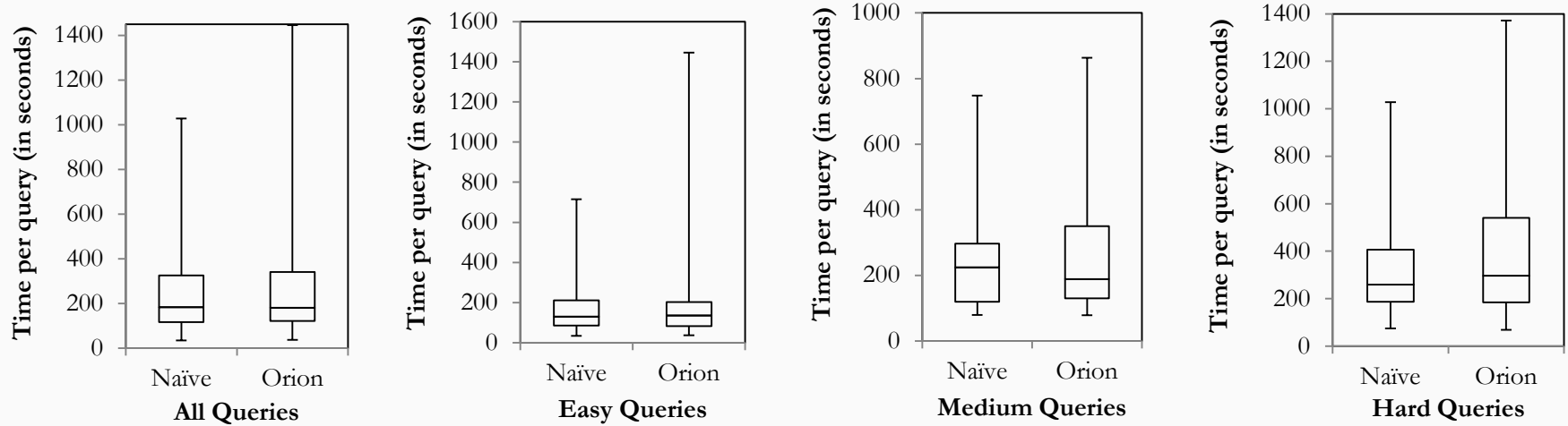
## Conversion Rate:

- Percentage of query tasks completed successfully
- Successful completion measured using edge isomorphism, and not a binary notion of matching

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

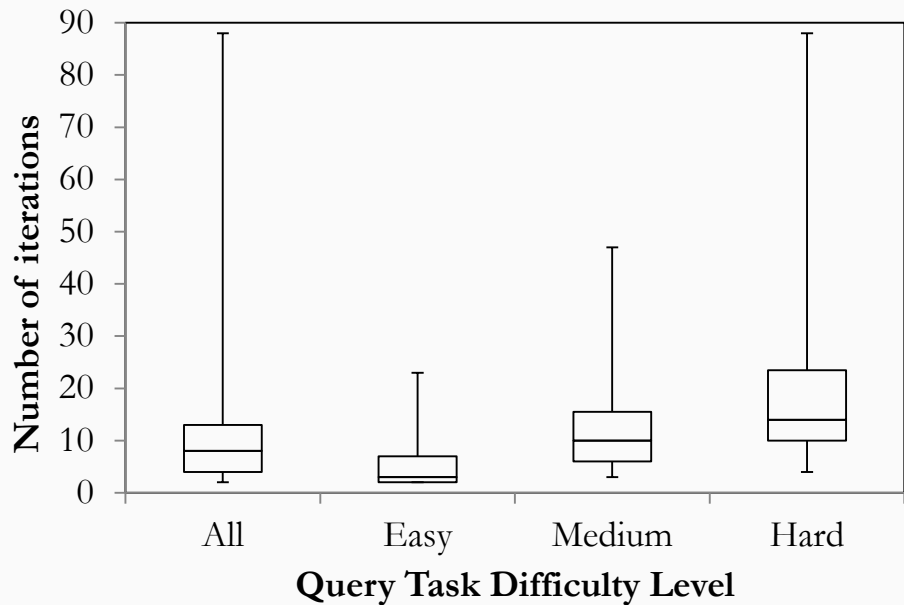
Orion has a higher conversion rate than Naïve for complex queries!

# User Studies: Efficiency by Time



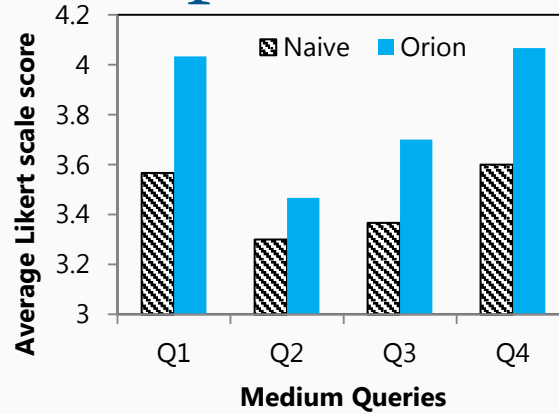
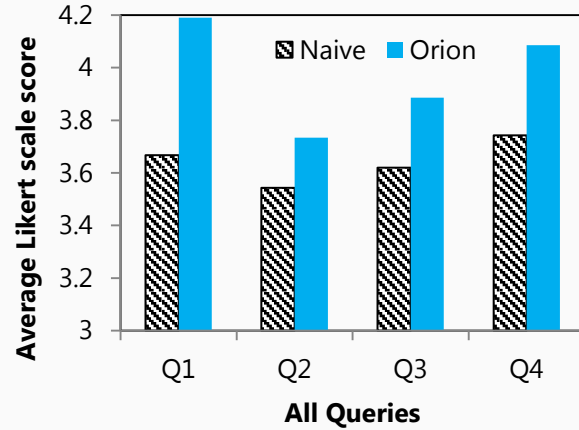
Time required to construct query graphs in Orion is comparable to Naïve in most cases, despite the steeper learning curve of Orion due to more features

# User Studies: Efficiency by Number of Iterations

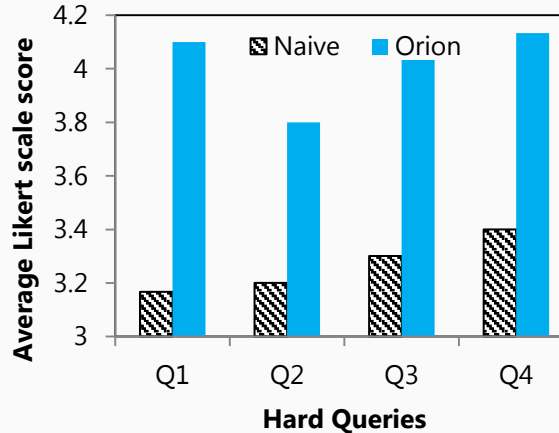
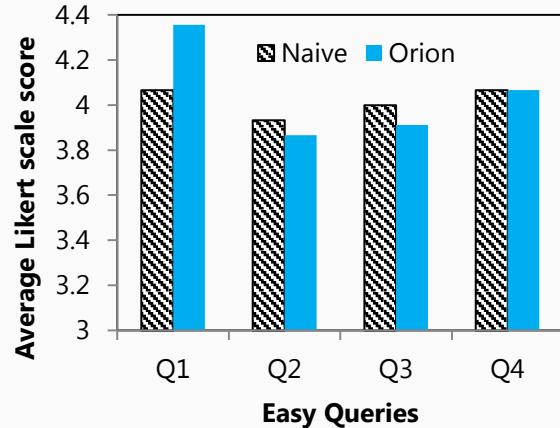


Time required to construct query graphs in Orion is comparable to Naïve in most cases, despite the steeper learning curve of Orion due to more features

# User Studies: User Experience Results



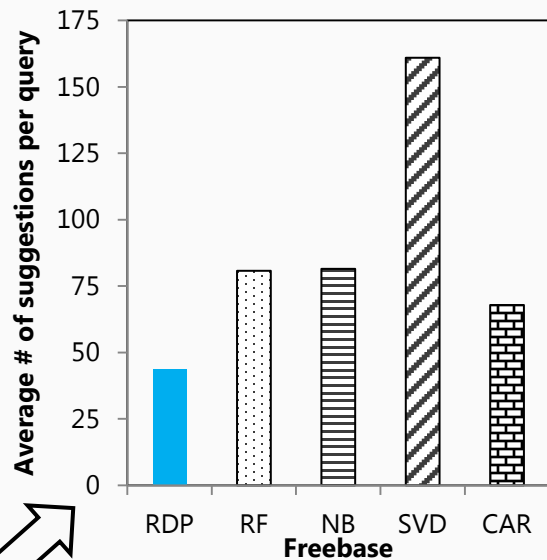
As the difficulty level of the query graph being constructed increases, the usability of Orion seems significantly better than Naive's



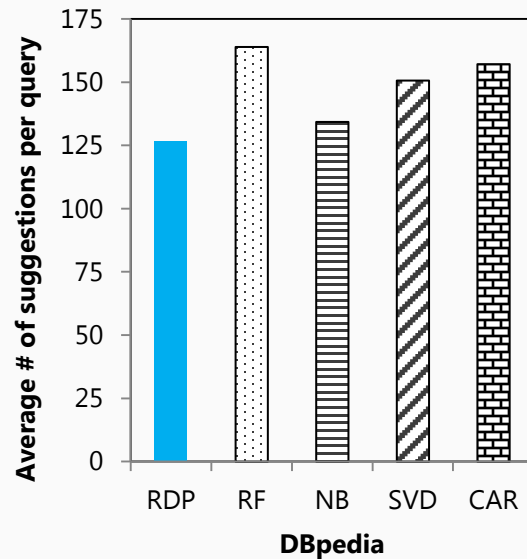
# Edge Ranking Algorithms

- Simulates only Passive Mode
- 43 target query graphs for Freebase
  - 6 two-edged, 10 three-edged, 9 four-edged, 17 five-edged, 1 six-edged (includes medium and hard queries from the user study)
  - 167 input instances
- 33 target query graphs for DBpedia
  - 2 three-edged, 29 four-edged, 2 five-edged
  - 130 input instances

# Edge Ranking Algorithms: Efficiency by Number of Suggestions



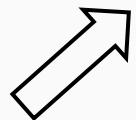
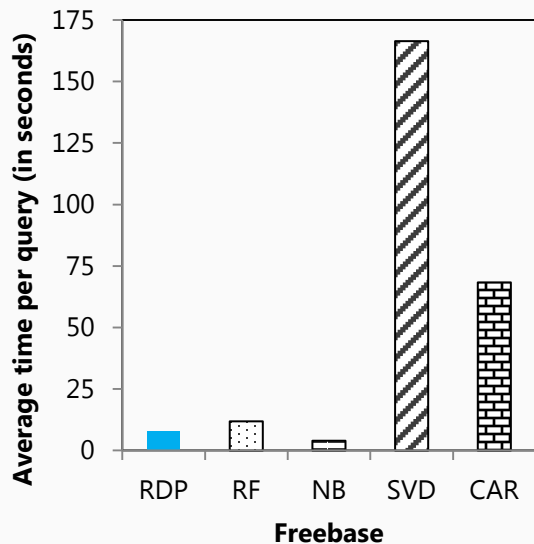
RDP requires only 40 suggestions, 1.5-4 times fewer than other methods



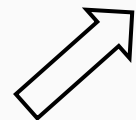
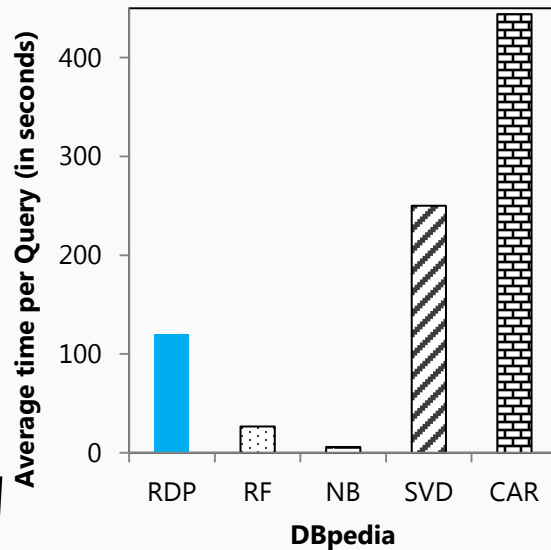
RDP requires fewer suggestions compared to all other methods



# Edge Ranking Algorithms: Efficiency by Time

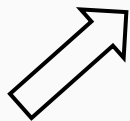
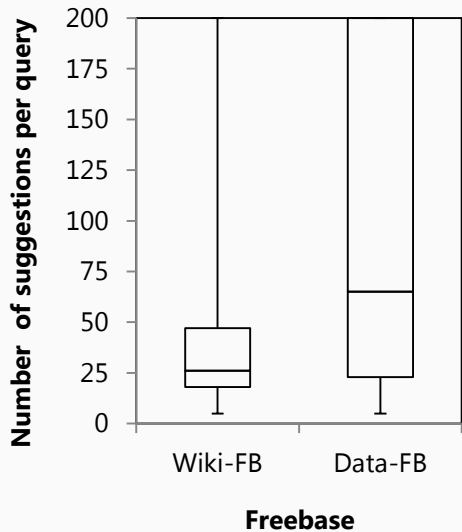


RDP better than RF and comparable to NB, despite RF and NB being light models

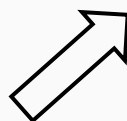
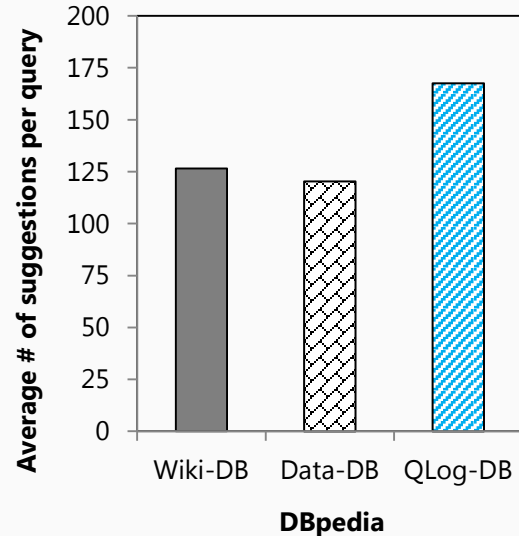


RDP significantly better than SVD and CAR, but worse than RF and NB

# Query Logs Comparison

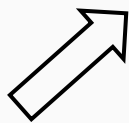
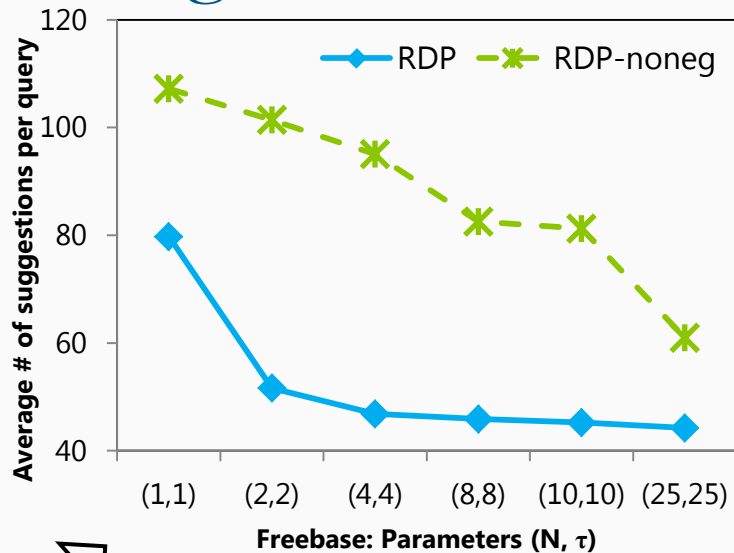


Positive edges better captured based on the context of human usage of relationships in Wikipedia

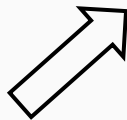
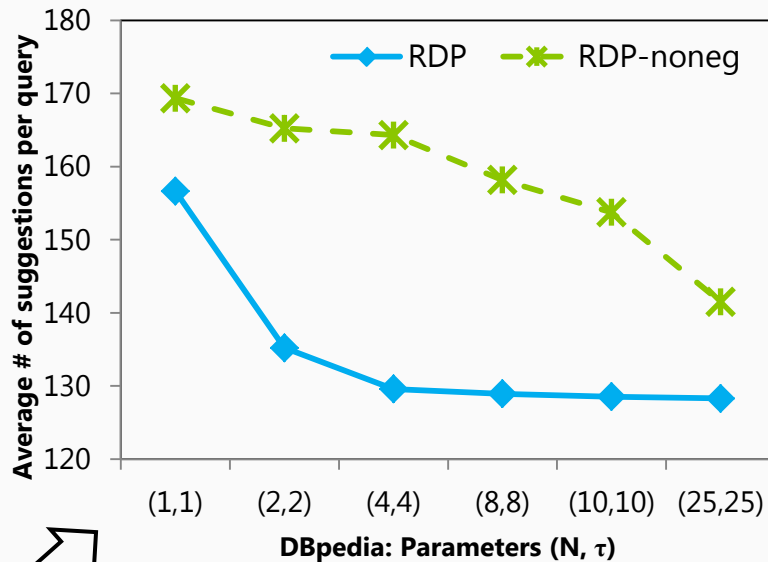


DBpedia is created using info-boxes in Wikipedia, and is thus very clean. Wiki-DB is highly similar to Data-DB for DBpedia

# Tuning RDP Parameters



RDP performs better with more random decision paths and higher query log threshold



Considering negative edges in query session is important, as it results in better performance of RDP

# Orion Contributions



Unique visual query builder with suggestions

Edge ranking algorithm : random decision paths

Query log simulation

Extensive user studies and experiments

Prototype available



# GQBE: Graph Query by Example

Prototype

<http://idir.uta.edu/gqbe>



Introduction Video

<http://bit.ly/1PLqLTD>



# GQBE GUI



Ranked similar  
answer tuples

















Keyword completion  
powered query interface



Graph Query by Example

Other Matching Answers

#	Donald Knuth	Turing Award
1	 Edsger Dijkstra	 Turing Award
2	 Peter Naur	 Turing Award
3	 Robert Tarjan	 Turing Award
4	 Alan Kay	 Turing Award
5	 John Hopcroft	 Turing Award
6	 Niklaus Wirth	 Turing Award
7	 Marvin Minsky	 Turing Award

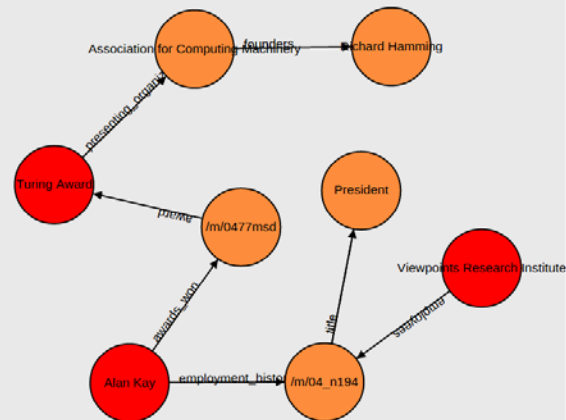
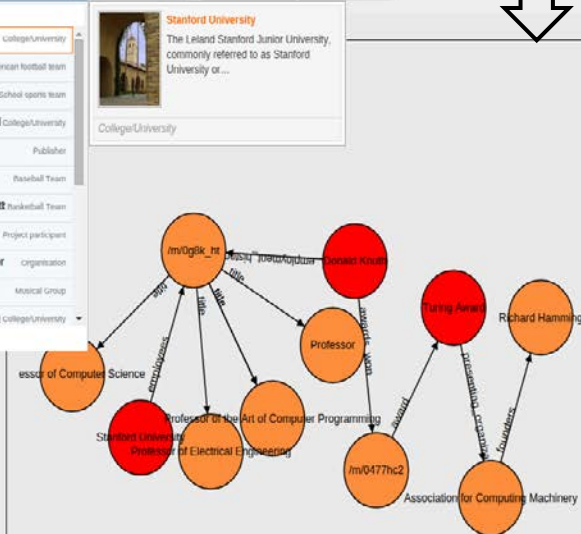
clear graphs

render graphs

Query graph automatically  
discovered by the system



An example answer graph





# TableView: Generating Preview Tables for Entity Graphs

# TableView

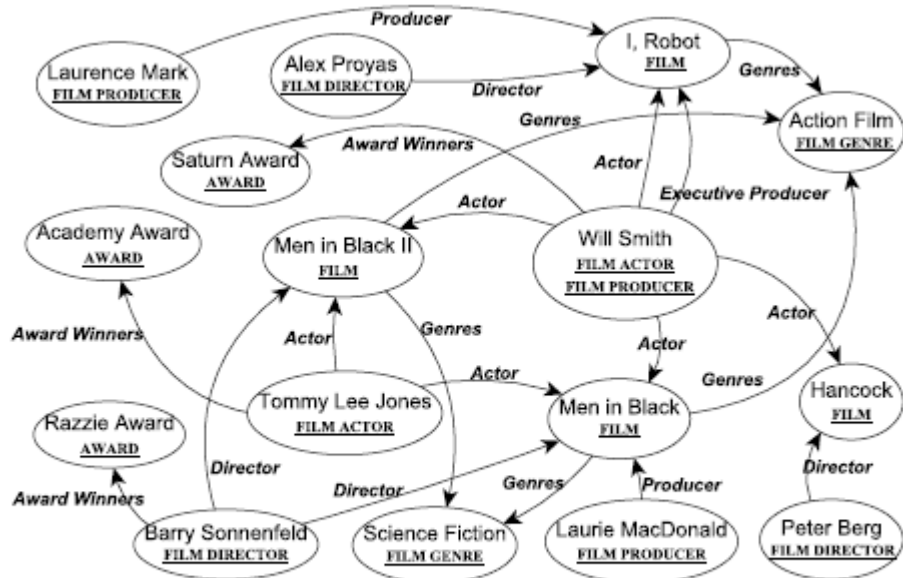


Figure 1: An Excerpt of an Entity Graph.

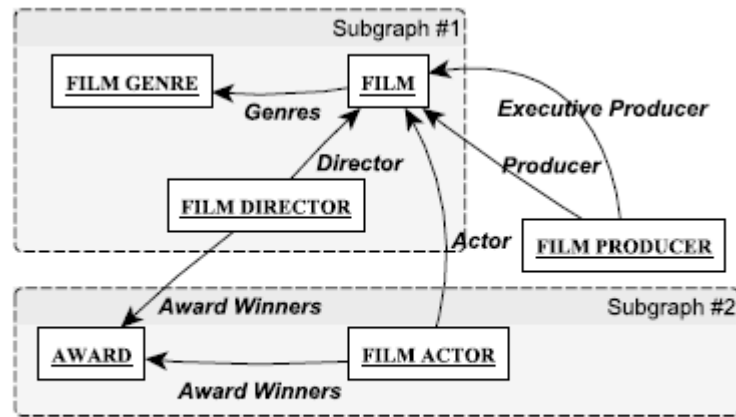


Figure 3: The Schema Graph for the Entity Graph in Fig. 1.



# TableView



	<u>FILM</u>	<i>Director</i>	<i>Genres</i>
$t_1$	Men in Black	Barry Sonnenfeld	{Action Film, Science Fiction}
$t_2$	Men in Black II	Barry Sonnenfeld	{Action Film, Science Fiction}
$t_3$	Hancock	Peter Berg	-
$t_4$	I, Robot	Alex Proyas	{Action Film}

	<u>FILM ACTOR</u>	<i>Award Winners</i>
$t_5$	Will Smith	Saturn Award
$t_6$	Tommy Lee Jones	Academy Award

**Figure 2: A 2-Table Preview of the Entity Graph in Fig. 1. (Upper and lower tables for subgraphs #1 and #2 in Fig. 3, respectively.)**

# Publications



## Overview

- Intuitive and Interactive Query Formulation to Improve the Usability of Query Systems for Heterogeneous Graphs. Nandish Jayaram. VLDB 2015 PhD Workshop.

## Orion

- Auto-Suggestion Based Visual Interface for Interactive Query Construction on Ultra-Heterogeneous Graphs. Nandish Jayaram, Rohit Bhooiplam, Chengkai Li, Vassilis Athitsos. Under preparation.
- VIIQ: Auto-Suggestion Enabled Visual Interface for Interactive Graph Query Formulation. Nandish Jayaram, Sidharth Goyal, Chengkai Li. PVLDB, 8(12): 1940-1943, August 2015. Demonstration description.

## GQBE

- Querying knowledge graphs by example entity tuples (Extended Abstract). Nandish Jayaram, Arijit Khan, Chengkai Li, Xifeng Yan, Ramez Elmasri. ICDE 2016 (TKDE Poster)

# Publications



## GQBE (cont'd)

- [Querying knowledge graphs by example entity tuples](#). Nandish Jayaram, Arijit Khan, Chengkai Li, Xifeng Yan, Ramez Elmasri. TKDE, 27(10): 2797-2811, October 2015.
- [GQBE: Querying knowledge graphs by example entity tuples](#). Nandish Jayaram, Mahesh Gupta, Arijit Khan, Chengkai Li, Xifeng Yan, Ramez Elmasri. ICDE, pages 1250-1253, 2014. Demonstration description.
- [Towards a query-by-example system for knowledge graphs](#). Nandish Jayaram, Arijit Khan, Chengkai Li, Xifeng Yan, Ramez Elmasri. GRADES 2014.

## TableView

- [Generating Preview Tables for Entity Graphs](#). Ning Yan, Abolfazl Asudeh, and Chengkai Li. Technical Report, arXiv:1403.5006, March 2014.

# Acknowledgment

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# Thank You! Questions?

- <http://ranger.uta.edu/~cli>  
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- Prototypes

<http://idir.uta.edu/orion>

<http://idir.uta.edu/gqbe>

